

Soil properties resulting in superior maize yields upon climate warming

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Abstract The impacts of global climate warming on maize yield vary regionally. However, less is known about how soil modulates regionally-specific impacts and soil properties that are able to alleviate adverse impacts of climate warming on maize productivity. In this study, we investigated the impacts of multiple soil inherent properties on the sensitivity of maize yield ($S_{Y,T}$) to growing season temperature across China. Our results show that a 1°C warming resulted in the largest yield decline ($11.2 \pm 6.1\%$) in the mid-eastern region, but the moderate yield increase ($1.5 \pm 2.9\%$) in the north-eastern region. Spatial variability in soil properties explained around 72% of the variation in $S_{Y,T}$. Soil organic carbon (SOC) content positively contributed the greatest extent (28.9%) to spatial variation of $S_{Y,T}$, followed by field capacity (9.7%). Beneficial impacts of increasing SOC content were pronounced in the north-eastern region where SOC content ($11.9 \pm 4.3 \text{ g kg}^{-1}$) was much higher than other regions. Other soil properties (e.g plant wilting point, sand content, bulk density, and saturated water content) were generally negatively correlated with $S_{Y,T}$. This study is the first one to answer how soil inherent properties can modulate the negative impacts of climate warming on maize yield in China. Our findings highlight the importance of SOC in alleviating adverse global warming impacts on maize productivity. To ensure food security for a rapidly increasing population under a changing climate, appropriate

farming management practices that improve SOC content could reduce risk of adverse effects of global climate warming through a gain in yield stability and more resilient production in China's maize belt.

Key words: climate crisis; sensitivity analysis; soil inherent properties; maize yield; China cropping belt; soil organic carbon

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1 Introduction

With a rapidly increasing global population and growing food demand, farmers are facing a dilemma of producing crops with higher yield in the same (or even less) cultivated areas (Cammarano and Tian, 2018; Harrison et al., 2012). More specifically, the mean growth rate of global crop yield must exceed 2.4% per year to feed 10 billion people by 2050s (Ray et al., 2013), without degrading natural resources (water, air, biodiversity, etc.) or producing additional greenhouse gas emissions (Alcock et al., 2015; Harrison et al., 2014a). However, the ongoing climate change and increasingly severe extreme climatic events are preventing farmers from fulfilling this goal. As current farming systems have evolved to fit within historical climate conditions, climate change-induced changes of meteorological factors, in particular rising temperature, are expected to pose significant risks for future farming outputs (Chang-Fung-Martel et al., 2017; Zhao et al., 2017). Understanding the impacts of shifting meteorological factors can provide invaluable information to improve farming's resilience to climate change, thereby enhancing food security while preserving the natural resource base (Harrison et al., 2021).

Temperature is a major determinant of crop productivity and crop phenological responses to climate warming have been well studied from local through to global scales. Asseng et al. (2015) estimated that global wheat production is likely to fall by 6% when annual temperature increases by 1°C, based on simulations from process-based crop models. Lobell and Field (2007) demonstrated a negative response of global maize yield to increased temperature through an analysis of global recorded maize yield for 1961-2002. Nevertheless, the actual impacts of increased temperature on crop yield are usually not uniform across regions. For example, maize crops had heterogeneous sensitivities in different regions, e.g. positive in South American yet negative in northwest Africa during 1961-2014 (Liu et al., 2020). Even within a country, the impacts can also vary greatly. For example, positive impacts were mainly distributed in northeast China from 1980 to 2010, while negative impacts occurred in most areas of central China (Chen et al., 2011; Deng et al., 2020). It has been reported that regional disparities in crop yield impacts are related to latitudes, which present different initial meteorological conditions (Deryng et al., 2014). Nevertheless, different regions also share varied soil properties that are also likely contribute to spatial variations. However, the extent to which soil properties modulate the impact of climate warming on crop yields is yet unknown.

In any cropping system, the suitability of a region for crop cultivation is determined by climate, yet the yield level is subject to soil characteristics as well (Bodner et al., 2015; Pinheiro et al., 2019). Soil plays a fundamental role in crop growth by providing physical support and more importantly, acting as the source of water and nutrients (Bonfante and Bouma, 2015). Such capabilities are based on a suite of physical, hydraulic, and chemical properties, which can show significant spatial variation (Ara et al., 2021; Harrison et al., 2011). Given the interacting nature of the soil-plant system in response to atmospheric drivers, crop response to climate warming is expected to vary spatially with different soil properties. Most soil properties are relatively stable and change slightly under short-term farming practices. Some of them, such as texture, water retention, and soil organic carbon (SOC) concentration, have been demonstrated to account for the spatial variability of crop responses to increased temperature (Farina et al., 2021; Sándor et al., 2020). For example, yields of seven major crops between 1958 and 2019 in the United States were generally more sensitive to temperature variability in coarse-textured soils and less responsive in medium- and fine- textured soils (Huang et al., 2021a). Rezaei et al. (2018) also reported that wheat yield on sandy soils decreased significantly by 24% with increased air temperature at anthesis, compared to loamy soils or soils consisting of clay in a controlled environment. In addition, SOC is an important indicator of soil quality and soils with higher SOC tend to show better water and nutrient retention (Karhu et al., 2011), which can then help crops buffer the impacts of increased temperature and even exploit positive effects (Droste et al., 2020; Song et al., 2015). However, the quantitative impacts of various soil properties on crop yields at a regional scale remain uncertain.



Figure 1 Maize cultivation in northeast China (photographs by the authors). Images show the farming practices of straw mulching and no-tillage, as strategies to improve soil quality.

With the largest cropping area in the world, China is one of the world's leading maize producers (FAOSTAT, 2020). However, China is also the world's most populous country. Against a background of global warming, sustainable intensification of maize production without adverse environmental trade-offs (Harrison et al., 2021) is of great importance for Chinese both domestic food supply as well as global food security. Here for the first time, we used the Agricultural Production Systems sIMulator (APSIM), to investigate impacts of multiple soil properties on the responses of maize yield to growing season temperature in China's Maize Belt (CMB). Our objectives were to address the following questions: I) how does maize yield respond to climate warming in different zones of CMB? II) how do various soil physical, hydraulic, and chemical properties modulate the impacts of climate warming on maize yield? By answering these questions, we provide insights into the development of adaptive strategies for global warming from the perspective of soil amelioration (Figure 1).

2 Materials and methods

2.1 Study area

The study area is CMB (Fig. 2), accounting for over 70% of national maize production and more than 15% of global production (Meng et al., 2016). CMB is confined to a relatively narrow band of land, spreading from the southwest to the northeast (97.6°-134.9°E, 21.4°-50.9°N). The characteristics of topography and climate vary greatly across CMB. Topographically, the western and south-western parts of CMB are occupied by plateaus with elevation more than 1000 m, but the eastern and north-eastern parts are mostly plains of less than 500 m. Climatically, CMB is characterized by warm and wet conditions in the south-western part, and cold and dry conditions in the north-eastern part. Varied environmental conditions result in varied cropping systems, e.g. single cropping system with maize in the northeast and northwest but double cropping system with winter wheat and summer maize in the middle of CMB. In addition, there is a mixed cropping system in the southwest, with both single and double cropping systems distributed. Thus, to consider the impacts of regional variations in climate and soils, we divided CMB into six maize planting regions (Fig. 2) according to a previous study (Huang et al., 2020). The regions were divided based on geographic location and different cropping systems, which were derived from agrometeorological observational data. Basic information of the six regions is given in Table 1.

The SPAM (Spatial Production Allocation Model) global synergy cropland map was used to distinguish the maize crop land (Lu et al., 2020). This map was developed by Chinese Academy of Agricultural Sciences based on a self-adapting statistics model with multiple existing maps and national and subnational statistics fused. It shows higher accuracy and better consistency (99%) with statistics than many previous cropland maps. This map was originally at a resolution of 5 arc-minute, but we upscaled to 15 arc-minute to make it match with climate data. As shown in Fig. 2, there were 4283 grids in total (Table 1) which illustrated cropland pixels over CMB. Our subsequent data analysis and result visualization were both performed on these maize cropland pixels.

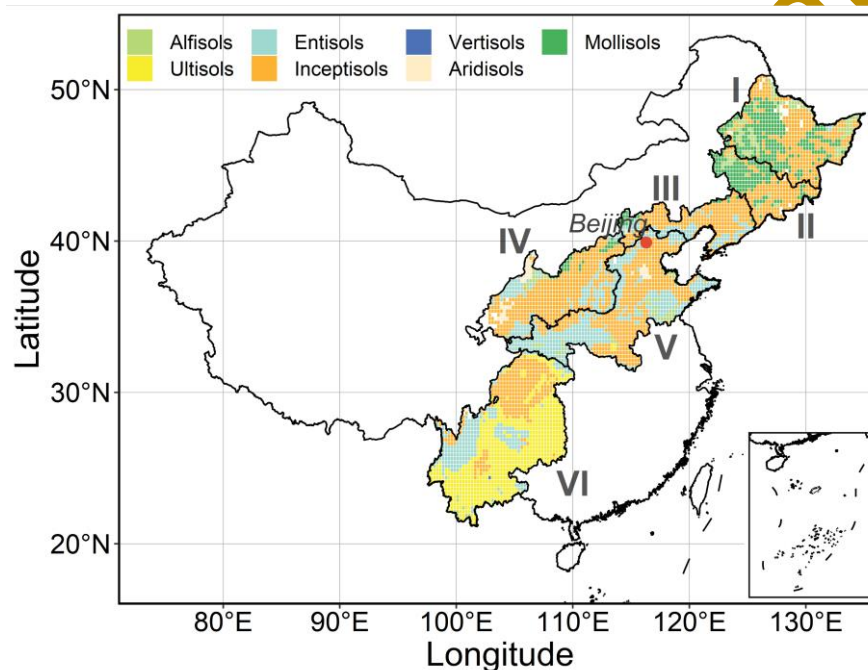


Figure 2 Six major maize cultivating regions across China's Maize Belt. Grid colours denote soil types based on the classification of the FAO-UNESCO (Food and Agriculture Organization of the United Nations-United Nations Educational, Scientific and Cultural Organization) Soil Map of the world (<https://www.fao.org/soils-portal/en/>).

Table 1 Climatic and growth information of the six maize regions across China's Maize Belt. CS: Cropping system; TGS: typical growing season of maize; AE: average elevation; AMT, AMP, and AMR are annual mean temperature, precipitation, and solar radiation, respectively.

Region	No. of grids	CS	TGS	AE (m)	AMT (°C)	AMP (mm)	AMR (MJ·m ⁻²)
I	713	Single	1 May – 30 Sep	267	2.1	550	15.8
II	338	Single	1 May – 30 Sep	387	4.6	620	16.6
III	375	Single	1 May – 30 Sep	529	6.9	589	17.6
IV	680	Single	1 May – 30 Sep	1471	8.5	458	19.0
V	950	Double	1 Jun – 30 Sep	388	13.2	677	17.9
VI	1227	Mixed	1 Apr – 30 Sep	1380	15.6	1120	18.2

2.2 Climate data

Historical gridded climate data were obtained from the Terrestrial Hydrology Research Group at Princeton University (Sheffield et al., 2006). This dataset was developed by blending the NCEP–NCAR (National Centers for Environmental Prediction–National Center for Atmospheric Research) reanalysis data with multiple observation-based datasets. Known biases in the reanalysis data have been corrected using observed data. The final product provides a globally-consistent dataset of near-surface meteorological factors at 15 arc-minute spatial resolution, which are designed for the purpose of long-term and broad scale terrestrial modelling studies (Parkes et al., 2019; Ruane et al., 2021). This dataset has also been implemented for many modelling studies in China and given satisfactory simulation results (Li et al., 2019; Yao et al., 2018). We derived daily series of maximum and minimum air temperatures, precipitation, and solar radiation (1961–2016) for all of the grids located in CMB.

2.3 Soil data

Gridded soil profiles for crop model simulation were derived from the Global High-Resolution Soil Profile Database of the Harvard Dataverse (Hengl et al., 2014). This dataset is an improved version of the SoilGrids dataset released by ISRIC (International Soil Reference and Information Centre) in 2014, with more soil hydraulic properties (e.g. soil water content at saturation, wilting point, and field capacity) included, making it readily available for simulating crop growth. Other soil physical and chemical properties, such as bulk density, texture, and organic carbon content, are also available and have been frequently used as inputs for crop modelling studies, including China (Wang et al., 2020; Zhang et al., 2018). In all grids, the soil profiles have six layers, namely 0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–

100 cm, and 100-200 cm. Spatial maps of several soil properties for each layer are given in the supplementary material (Figures S1-S6). In addition, these data are provided for each country at 5 arc-minute resolution. To make them congruent with the climatic grids, we aggregated 5 arc-minute grids into 15 arc-minutes.

2.4 APSIM simulations

We implemented the APSIM (Agricultural Production System sIMulator, <https://www.apsim.info/>) crop model version 7.10 to simulate the dynamics of maize growth and development. APSIM is structured around soil, plant, atmosphere, and management modules, making it a comprehensive model capable of simulating manifold biophysical processes in response to environmental variations (Holzworth et al., 2014). Many studies have successfully used the APSIM maize module to quantify the impacts of climate change on maize yield in China (Wang et al., 2018; Xiao et al., 2020; Zhu et al., 2022).

The APSIM model was originally developed in Australia but since inception has been used with success in numerous countries across the world (Harrison et al., 2014b). When used in other regions, cultivar traits should be re-parameterized only if local and robust datasets exist (Harrison et al., 2012; Harrison et al., 2019). In this study, we obtained the genetic parameters of six maize genotypes (Table S1) for the six cultivating regions from the study of Huang et al. (2020), who reported that the calibrated maize genotypes can well represent observed yield of maize cultivated in the belt with R^2 being 0.74 and NRMSE being 17.7%. Then we set up a long-term simulation (1961-2016) for each grid across CMB. Climate and soil inputs for each grid have been described above. Sowing date was determined as multi-year average sowing date of the nearest agrometeorological observational site for each grid (Huang et al., 2020). Details can be found in Figure S7. Maize planting density, depth, and row space were same for all regions, i.e. 67,500 plants ha^{-1} , 5 cm, and 60 cm, respectively. The fertilizer at sowing was 180 kg ha^{-1} urea-based N. These are common farming management practices across China (Huang et al., 2022; Ren et al., 2016; Zheng et al., 2021). With same management practices across regions, we were able to focus on the effects of climate and soil on maize yield in subsequent analysis.

It should be noted that climate, soil, cultivar, and management practices have been changing during past decades. Nonetheless, we did not focus on the effects of cultivar change but on the responses of current

maize planting to climate change. Thus, we used one calibrated cultivar and kept soil inherent properties and other management practices constant over the study period. Moreover, to exclude any ‘carry-over’ effects from previous seasons, initial soil water and nitrogen were reset to 20% of maximum soil available water and 80 kg ha⁻¹ NO₃-N and 12.5 kg ha⁻¹ NH₄-N on the 1st of January each year. Fallow was performed prior to sowing.

2.5 Identification of temperature sensitivity

We implemented a widely-used panel data model, ordinary least squares regression with quadratic terms (Deng et al., 2020; Schlenker and Lobell, 2010; Zhu et al., 2019), to estimate temperature sensitivity of maize yield ($S_{Y,T}$). Growing season mean temperature (T), total precipitation (P), and mean solar radiation (R) were used as the explanatory variables.

$$\ln(Yield_{i,t}) = a_1 T_{i,t} + a_2 T_{i,t}^2 + b_1 P_{i,t} + b_2 P_{i,t}^2 + c_1 R_{i,t} + c_2 R_{i,t}^2 + \varepsilon \quad (1)$$

where $\ln(Yield_{i,t})$ is the natural logarithm of yield at grid i in year t . As the APSIM model simulated maize yield can be viewed as climate-driven yield, we did not normalise for longitudinal yield gains associated with technological progress (e.g. breeding, fertilizer, and pesticide application). Quadratic terms are included for three climatic variables to simulate their nonlinear impacts on maize yield. a , b , and c are regression coefficients. ε represents the model error term. Then the $S_{Y,T}$ can be defined as

$$S_{Y,T} = \frac{\partial Y}{\partial T} \cdot 100\% = (a_1 + 2a_2 \bar{T}_i) \cdot 100\% \quad (2)$$

where \bar{T}_i denotes the mean temperature during the study period 1961-2016 in grid i . a_1 and a_2 stand for the regression coefficients derived from equation (1). As the response variable (maize yield) has been log-transformed, the estimated temperature sensitivity indicates the percentage change of yield for 1°C warming. We calculated the $S_{Y,T}$ for all of the grids across CMB using equations (1) and (2). The performance of the model was evaluated using two metrics, namely coefficient of determination (R^2) and Normalized Root Mean Square Error (NRMSE), given by following equations:

$$R^2 = \left(\frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^n (P_i - \bar{P})^2}} \right)^2 \quad (3)$$

$$NRMSE = \frac{1}{\bar{O}} \sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - P_i)^2} \quad (4)$$

where n is the number of samples, O_i and P_i denote observational and predicted values, and \bar{O} represents the mean of observational values. Generally, the model with higher R^2 and lower NRMSE is considered to be a better-performance model.

2.6 Contributions of soil properties to temperature sensitivity

We implemented the Random Forest (RF) to study the contributions of various soil properties to temperature sensitivity. RF, also known as random decision forest, is an advanced tree-based ensemble machine learning algorithm (Breiman, 2001). Except for developing predictive regression or classification models, RF is also commonly used for investigating the complicated relationships among variables, as it can account for nonlinear and hierarchical relationships between the response and predictor variables (Dibari et al., 2020). For this purpose, two built-in functions, namely variable importance measures and partial dependence plots, can be employed after a RF model has been built. In this study, we first built a RF regression model with temperature sensitivity as the dependent variable and multiple soil properties as independent variables. The accuracy-based importance metric was used to evaluate variable importance. This was generated using an out-of-bag (OOB) validation procedure. In brief, during the model building phase, about one third of all input values were randomly selected and set aside for subsequent OOB model validation. Then, the prediction accuracy on the OOB sample was determined. The mean decrease in prediction accuracy when the values of a certain variable in the OOB sample were randomly shuffled, was defined as the importance value of the variable (Heung et al., 2014), expressed as the mean square error (MSE):

$$MSE_{OOB} = \frac{1}{n} \sum_{k=1}^n (K_i - \bar{P}_{kOOB})^2 \quad (5)$$

where n denotes the number of observations, K_i indicates known value, and \bar{P}_{kOOB} represents the average of all OOB predictions across all trees.

We also used partial dependence plot (PDP) to evaluate the marginal effects of a selected explanatory predictor on the response variable. A PDP can show whether the relationship between the response and a predictor is linear, monotonic or more complex, marginalizing over the values of all other input predictor variables (the ‘complement’ features) (Friedman, 2001). In this study, we used the

‘randomForest’ package sourced in the R software to build the RF model and derived variable importance values and PDPs.

3 Results

3.1 Climatic and yield trends from 1961 to 2016

Temporal trends of climate and simulated maize yield in all the grids over CMB for the period of 1961–2016 are illustrated in Figure 3. A significant increasing trend was detected for growing season mean temperature in nearly all central and northern grids. Specifically, temperature increased faster in inland grids ($>0.2^{\circ}\text{C}/10\text{a}$). The trends varied in the southern region (region VI), with a part in its east showing decreased temperature. Solar radiation significantly increased in central regions and parts of north-eastern regions, with a trend over $0.2 \text{ MJ m}^{-2}/10\text{a}$. The linear trends of solar radiation in remaining regions were not significant. For growing season total precipitation, no significant trends were detected in most of the regions. Maize yields generally increased in many grids, e.g. northern regions, part of mid-eastern regions, and the northeast part of the southern region (region VI). In some grids of central and southern regions (regions IV and VI), maize yield decreased. As model simulated maize yield were climate driven, it can be derived that yield trends were mainly attributed to climate variations during 1961–2016. In addition, as the trends of precipitation and solar radiation were not significant in most grids, we did not consider the yield sensitivity to them in subsequent analysis.

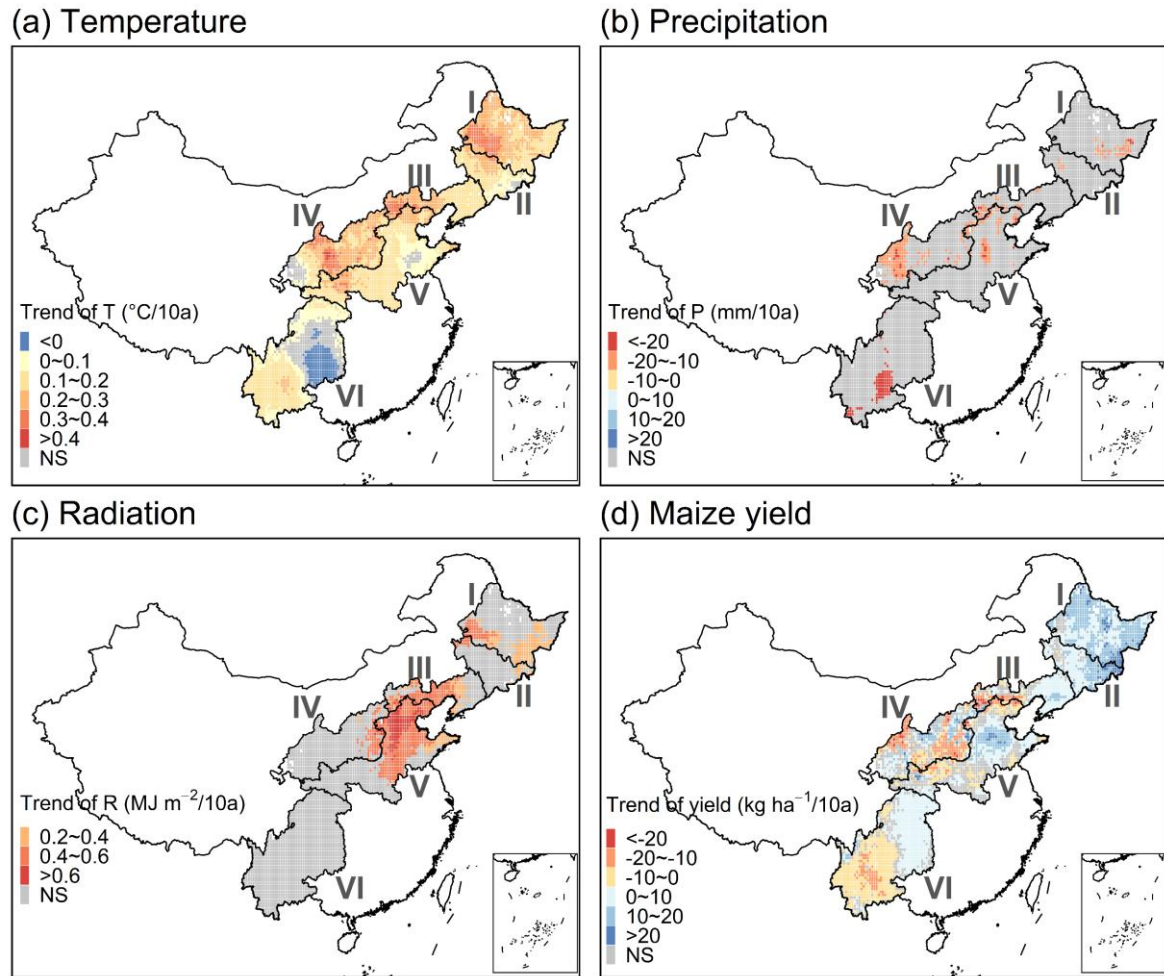


Figure 3 Linear trend of growing season mean temperature (a), precipitation (b), solar radiation (c), and maize yield (d) in each grid of China's Maize Belt for the period 1961–2016. NS: not significant ($P>0.05$). In addition, mean values of the four variables for the study period were illustrated in Figure S8.

3.2 Temperature sensitivity of maize yield

The performance of the panel data model in each region are presented in Figure 4. Though with some fluctuations, the R^2 values for the six regions were mainly around 0.5, and the NRMSE values were mainly lower than 1%, meaning that maize yield variations could be largely explained by climate variables.

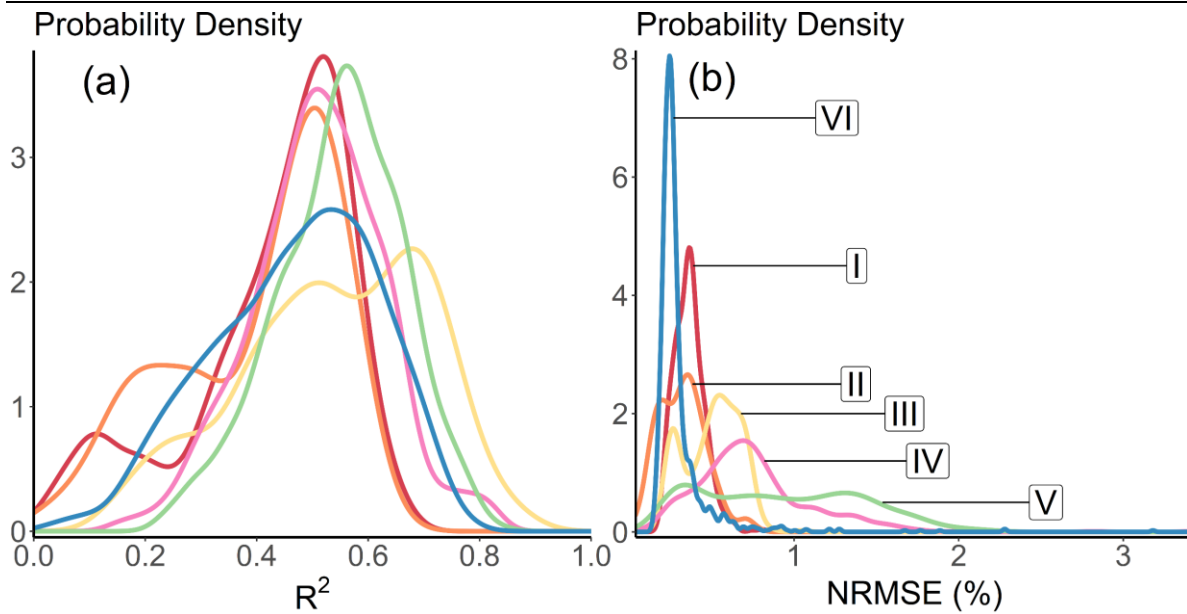


Figure 4 Distributions of R^2 (coefficient of determination) and NRMSE (Normalized Root Mean Square Error) derived from the panel data model for all grids in each region. The probability density curves are derived from gaussian kernel density estimate. The area under a density curve should sum up to a total of 1. They are smoothed versions of histograms, showing the distributions of continuous data. The peaks of a density curve help display where values are concentrated.

As rising temperatures are a uniform and consistent feature associated with climate change, we separately analyzed the contributions of temperature to maize yield (hereafter, temperature sensitivity or $S_{Y,T}$). The results for all the grids across the belt are illustrated in Figure 5. Temperature sensitivity varied greatly in different grids. The most noticeable feature was that $S_{Y,T}$ values in region V were rather smaller than other regions. Specifically, the values in region V were generally smaller than 0 and the mean value was about -11 %/°C. This indicated that maize yield in region V negatively responded to temperature increase and yield normally decreased by 11% for every 1°C increase. On the other hand, we also noticed that grids with positive temperature sensitivity were mainly located in the northeast, especially region I. Region I was the only one with mean $S_{Y,T}$ exceeded 0% per °C, reaching 1.5% per °C. The values in other regions generally showed a normal distribution with the mean values in the range of -5 to 0 %/°C. Thus, in general, temperature increase could contribute to yield losses in most regions of CMB, except for region I.

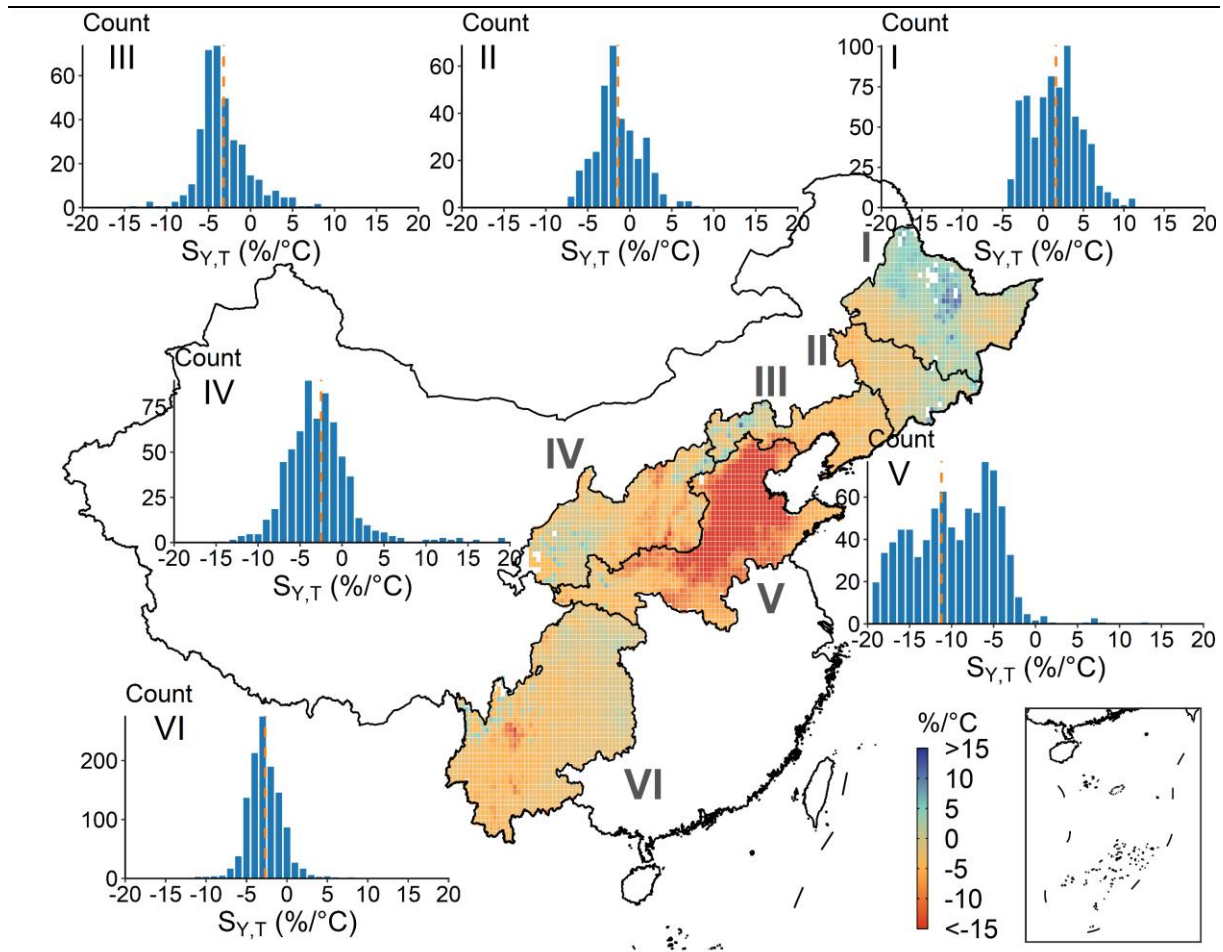


Figure 5 Spatial distributions of $S_{Y,T}$ (%/°C). $S_{Y,T}$ is the temperature sensitivity of maize yield, representing the yield change (%) for 1°C warming. Histograms show the distributions of $S_{Y,T}$ values for all grids in each sub-region. The vertical dotted line indicates the average of each region.

3.3 Impacts of soil properties on temperature sensitivity

Figure 6 shows the performance of the RF model in explaining the spatial variance of temperature sensitivity based on soil properties. We selected input soil properties according to three standards. First, they were APSIM parameters so that their impacts could be captured by modelling methods. Second, their characteristics did not change greatly under conventional farming management practices. Third, they were commonly available in gridded soil datasets. Thus, we selected six soil properties, namely soil organic carbon content (SOC), bulk density (BD), sand content (SC), wilting point (WP), field capacity (FC), and saturated water content (SWC). Weighted averages of these soil properties by layers were used as explanatory predictors to develop the RF model. The model explained 72% variation of

$S_{Y,T}$ with low error (2.74% $^{\circ}\text{C}^{-1}$), indicating that temperature sensitivity was largely under the modulation of soil inherent properties.

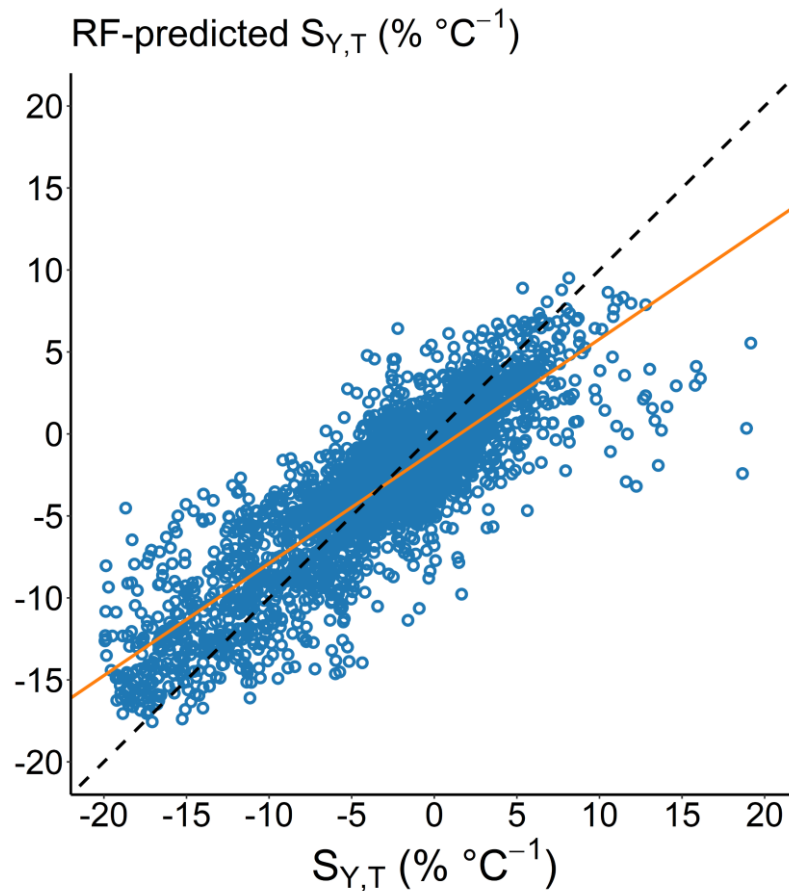


Figure 6 Comparison of RF-predicted $S_{Y,T}$ and actual $S_{Y,T}$ for all of 4283 grids across China's Maize Belt. The RF model was run based on a 10-fold cross validation procedure. The dashed line is the 1:1 ratio line. The orange line is the linear regression fit. Fitted equation $y=0.68x-1.06$, $R^2=0.72$, $\text{RMSE}=2.74\% \text{ }^{\circ}\text{C}^{-1}$. Comparisons of RF-predicted $S_{Y,T}$ and actual $S_{Y,T}$ for each sub-region are shown in figure S9.

Next, we analyzed the relative importance of input predictors through their marginal effects on temperature sensitivity (Figure 7). SOC ranked highest with an importance value of 28.9%, showing a positive effect on temperature sensitivity. While SOC content was highest in region I, it was lowest in region V, partly explaining the differences of temperature sensitivity in the two regions (Figure 7a). Next highest was wilting point (20.2%), showing a negative effect on temperature sensitivity (Figure 7b). Moreover, wilting point in region I was lowest, suggesting that this variable also contributed to the high temperature sensitivity of region I. Sand content and bulk density showed a similar negative impact

and their importance values were also similar (Figure 7c and d, noting that the bulk density in region I and V were larger than other regions). The latter two predictors were field capacity and saturated water content (Figure 7e and f), two hydraulic properties, showing positive and negative impacts on temperature sensitivity respectively. The two soil properties were similarly distributed across CMB, with region VI highest and region IV lowest.

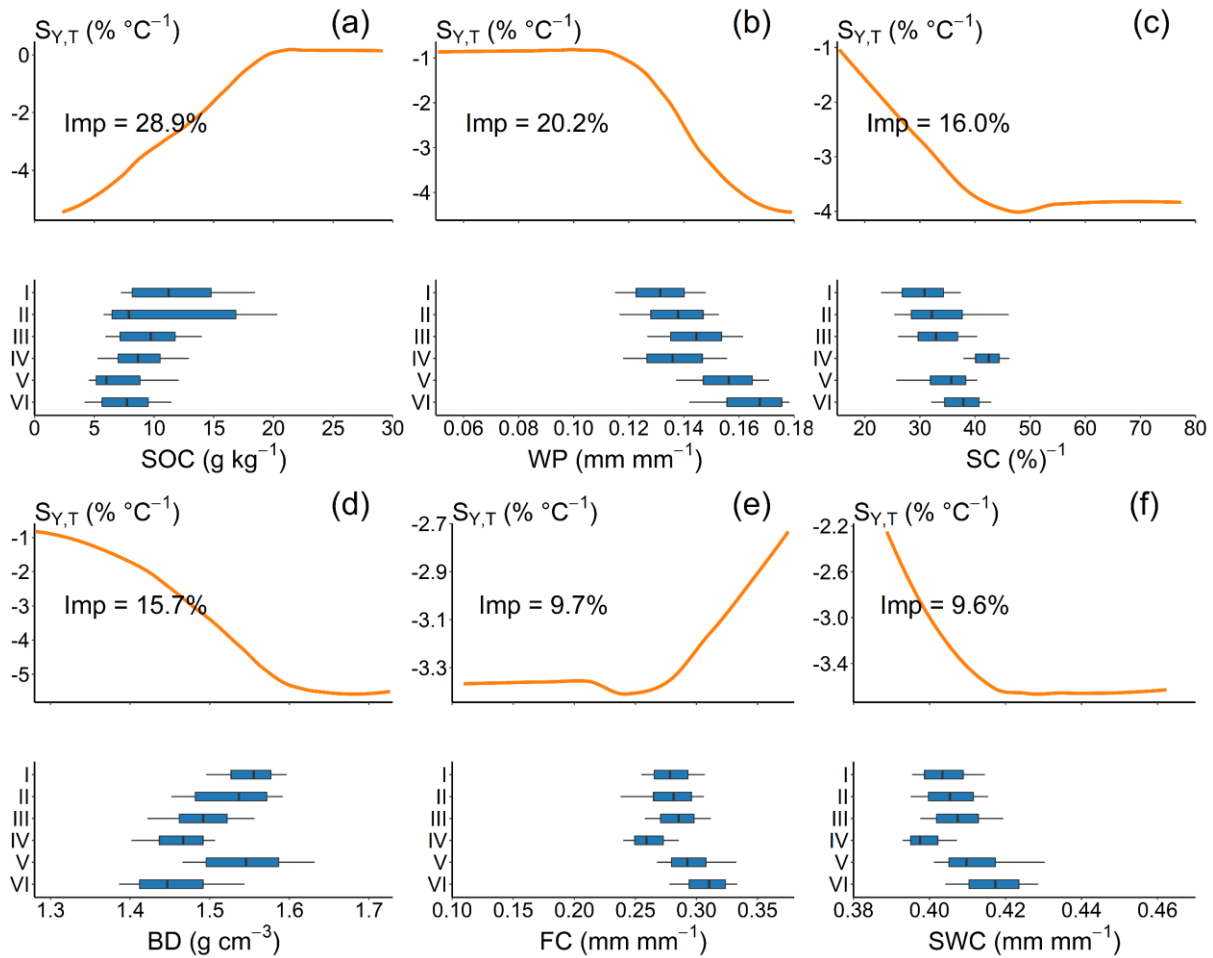


Figure 7 Partial dependence of $S_{Y,T}$ on input soil properties and distributions of each property in different regions. The orange lines are smoothed representations of the response. The trend of the line, rather than the actual values, describes the nature of the dependence between the response and predictors. The percentages denote the relative importance of each predictor generated from the random forest model. Box plots indicate the distributions of each soil property in different regions. Box boundaries indicate the 25th and 75th percentiles across grids, whiskers on the left and right of the box indicate the 10th and 90th percentiles. The black lines within each box indicate the median value. SOC, WP, SC,

BD, FC, and SWC represent soil organic carbon content, wilting point, sand content, bulk density, field capacity, and saturated water content, respectively. Regions I-VI correspond to those shown in Fig. 2.

4 Discussion

Ensuring food security is the second most important Sustainable Development Goals of the United Nations during the period of 2015-2030. The agriculture sector is struggling to fulfil this goal under the background of the climate crisis. Temperature increase is the typical feature of climate change. It is observed that global average land surface temperature has increased by $\sim 1^{\circ}\text{C}$ in comparison with 1850-1900 and is going to increase by another 0.5°C over the next 20 years (IPCC AR6). In our study, we also found increasing trends of growing season temperature in most grids of the CMB (Fig. 3), with some grids increasing even faster than global averages. Temperature has been previously reported as the predominant factor affecting maize yield (Lobell et al., 2011), thus any changes on temperature are likely to cause substantial impacts on maize yields. Our study revealed that for each unit increase in growing season mean temperature, the maize yield across the belt was generally reduced by 3.6% (Fig. 4). This is consistent with Deng et al. (2020)'s study which also reported a negative response of maize yield in China to climate warming. A main reason is that increased temperature hastens phenology and reduce the growth cycle, resulting in fewer days for yield formation (Casali et al., 2021; Ibrahim et al., 2019). Meanwhile, the adverse effects of high temperature are also associated with increased maintenance respiration rates (Innes et al., 2015) and decreased net photosynthesis (Rezaei et al., 2015). Nevertheless, we also noticed the positive impacts of climate warming on maize yield, specifically in north-eastern of the belt (Fig. 4). This might be related to antecedent low temperature conditions, under which increased temperature still lied within the optimum temperature range of $18\text{-}25^{\circ}\text{C}$ (Muchow et al., 1990) for maize growth and yield.

The soil-plant-atmosphere continuum is a connected holistic system (Harrison et al., 2012) such that changes in one part of the system influence feedbacks in other parts. Given this, we would expect soil properties to influence crop-climate responses, thereby contributing to the spatial variation in $S_{Y,T}$. This was confirmed by our results that in grids at a same latitude, the response of maize yield to rising temperature could also vary greatly (Fig. 4). Our results also illustrated that among multiple soil properties, SOC contributed most to the sensitivity of maize productivity to climate warming (Fig. 5),

in particular the resilience to warming. Many previous studies have demonstrated that crop yields are under the modulation of soil carbon stocks and higher SOC content can normally lead to higher pasture and/or crop yields (Harrison et al., 2021; Osanai et al., 2020; Stockmann et al., 2013). Here we further demonstrated that SOC could help buffer the adverse effects of climate warming. This might be related to the improvement of soil quality by SOC. Soil organic carbon content is a fundamental representation of soil quality (Lal, 2016), supporting multiple soil functions determining soil physical, chemical, and biological features (Reeves, 1997) which can significantly affect the productive ability of soils for food production. SOC correlates with multiple soil biodiversity dimensions, e.g. community structure, microbial biomass, and its activities (Mau et al., 2015). Decomposition of SOC mainly releases absorbable nitrogen and higher nitrogen contents has been previously demonstrated to provide resilience for maize to cope with warming (Deng et al., 2020). In addition, SOC can also increase soil structure (e.g. aggregate stability and porosity) and water retention (Bronick and Lal, 2005; Karhu et al., 2011). In this case, crops can normally obtain more available water to maintain high productivity via evapotranspiration during high temperature conditions (Huang et al., 2021a; Williams et al., 2016). Our results also show that wilting point largely accounted for the spatial variations of temperature sensitivity, more important than other two hydraulic features, field capacity and saturated water content. This might be also due to the differences of plant available water capacity (PAWC) in different regions. The PAWC is determined as the difference between field capacity and wilting point. In CMB, the variations of wilting point in different regions were relatively larger than field capacity (Fig. 5), thus it was the wilting point that accounted more for the variations of PAWC as well as $S_{Y,T}$. Sand content ranked third and it showed negative impacts of $S_{Y,T}$. This was consistent with results obtained by Rezaei et al. (2018), reporting that wheat yield reduced significantly by 24% grown on sandy soil substrate with increasing air temperature in a chamber-based experiment and with Van Ittersum et al. (2003)'s study monitoring a declined of wheat yield in a sandy soil under warmer (increase of temperature up to 3°C) scenarios in western Australia. This was mainly due to that high wilting point usually represented low water holding capacity (Huang et al., 2021a). Bulk density also showed negatively influenced $S_{Y,T}$, as higher bulk density normally resulted in lower soil porosity (Song et al., 2015).

Our results also reveal feasible, reversible pathways for farmers to take action against global climate change. Over the past few decades, intensive farming practices, e.g. excessive inorganic fertilization

and tillage, have been widely adopted to enhance crop productivity to meet the increasing domestic food demand in China. These practices degrade soil quality, meaning more unfavourable soil conditions for crops to grow (Droste et al., 2020; Waqas et al., 2020). Degraded soil quality will also make a cropping system more vulnerable to warming according to our results. These problems can be alleviated through improving soil quality. With appropriate farming management practices at long-term context, farmers can control soil quality (unlike the weather) to produce high crop yields under current climate conditions, as well as maintain yields despite climate change (Macholdt et al., 2020; Manns and Martin, 2018). For example, Song et al. (2015) conducted a 22-year field experiment in northeast China and claimed that compared to inorganic fertilizer treatments, organic matter amendments (crop straw or farmyard manure) can not only increase maize yield but also maintain an increasing trend. As demonstrated by Song et al. (2015), organic amendments can mitigate the negative and promote the positive effects of climate warming on maize production through increasing SOC. Farming practices that increase SOC can usually enable soils to keep higher levels of biodiversity, supply more plant nutrients, have better water holding capacity, and be less vulnerable to erosion (Manns and Martin, 2018; Minasny et al., 2017). Moreover, increasing SOC is identified as a main approach for greenhouse gas emissions mitigation (Farina et al., 2021; Lal et al., 2007), thus it can also contribute to the mitigation of climate change. In addition, some conservation agriculture practices, such as no tillage (Figure 1), are also proved to improve soil quality (Sithole et al., 2019; Valkama et al., 2020). Nevertheless, different regions might be varied in most suitable practices. Thus, further studies are needed to explore what farming practices can maximize the benefit to soil quality in certain regions to create resilient and sustainable agro-ecosystems in face of climate change.

5 Conclusions

This study is the first one to quantify the potential of soil inherent properties to mitigate the effects of increased growing season temperature on maize yield across the CMB. Climate warming caused yield losses (up to 20% decline for 1°C warming) in most areas but gains in north-eastern regions (up to 10% increase for 1°C warming). Around 72% of the spatial variation of yield sensitivity could be attributed to the variation in soil properties. Soil organic carbon contributed most to the temperature sensitivity of yield, with positive correlations. As previous intensive farming practices have been widely carried out

across the belt, soil degradation potentially reduced agriculture's resilience to climate warming and thus food security. Here we provided evidence that preservation of soil carbon and improved soil quality reduced yield losses due to climate warming.

Declarations

Authors' contributions Funding acquisition: Kelin Hu. Data collection and formatting: Puyu Feng, Mingxia Huang, and De Li Liu. Data analysis: Puyu Feng and Bin Wang. Writing original draft: Puyu Feng, Bin Wang, Matthew Tom Harrison, Jing Wang, Ke Liu, and Qiang Yu. Writing, review, and editing: all co-authors.

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Data availability The datasets generated during and/or analysed during the present study are available from the corresponding author on reasonable request.

Code availability Not applicable.

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