Building soil to reduce climate change impacts on global crop yield

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Abstract

Improving soil health and resilience is fundamental for sustainable food production, however the role of soil in maintaining or boosting crop productivity under climate change is still unclear. Here, we examined the role of soil in yield response to climate warming for four major crops (i.e., maize, wheat, rice and soybean), using global-scale datasets and machine learning techniques. We found that each °C of warming have reduced global yields of maize by 3.4%, wheat by 2.4%, rice by 0.3% and soybean by 5.0%, which are high spatial heterogeneous with positive impacts in certain regions. Soil organic carbon (SOC) would dominantly regulate negative yield responses. Improving SOC could build yield resilience to warming, avoiding an average of 3-5% $°C^{-1}$ of warming-induced yield loss over 60% of global planting area. The avoided loss of production in future could supply additional food for up to ~560 million people in 2050. Our findings highlight the critical role of soil in reducing warming impacts on food security, especially for developing regions, given that sustainable actions could be taken broadly.

Main

The number of people suffering from food insecurity continues to increase, with over 700 million people in total in 2020[1]. With a growing population and climate change, the global food demand in 2050 is expected to increase by 30% to 62% relative to 2010[2]. How to feed this future population and achieve the Sustainable Development Goals (i.e., zero hunger) is a major global challenge[3]. Maize, wheat and rice account for 89% of global cereal production, and soybean supplies 28% of the world's vegetable oil[1]. Climate change is threatening global crop production. Rising temperature has been proved to be a major cause for global yield losses[4-6], especially in less-developed and warm areas such as sub-Sahara Africa and Latin America[7]. Recent modeling studies have also shown that, without effective adaptation, warming may also reduce yields in cooler regions[4,8].

Strengthening adaptations of agricultural systems is imperative to reduce exposure and vulnerability to climate change[9]. Global assessments have mainly focused on cultivar shifts and agronomic management practices to enhance adaptation[10-12]. A combination of cultivars (e.g., higher heat tolerance) and management (e.g., soil organic matter management) adaptations could reduce yield losses due to warming by ~5% in the mid-21st century[13]. In terms of common adaptation strategies, cultivar switch and irrigation contribute significantly to crop yield gains[10]. However, the negative effects of climate change on crop production cannot be fully offset by implementing adaptation, especially in lower latitudes[9,13].

Resilient and productive soils are necessary to sustainably intensify agriculture, to increase yields while minimizing environmental harm[14,15]. High-quality soils can buffer climate variability in cropping systems and sustain yield stability[16,17]. Soil organic carbon (SOC), in particular, has been suggested as an integrated and representative indicator of soil quality, which relates to soil biological and physical properties such as disease suppressiveness, heat capacity[18,19] and soil heath, with important functions such as water retention and nutrient supply[20,21]. Improving SOC can help build climate resilience to reduce risks to food insecurity[22,23], and decrease reliance on irrigation and fertilizer application[24]. A recent study has revealed that increasing SOC can reduce the yield gaps of maize and wheat[14]. However, the role of soil in building crop yield resilience to climate change is still missing from the crop-soil-environment system, it remains difficult to quantify the complex interactions between soil, climate and yield[25,26].

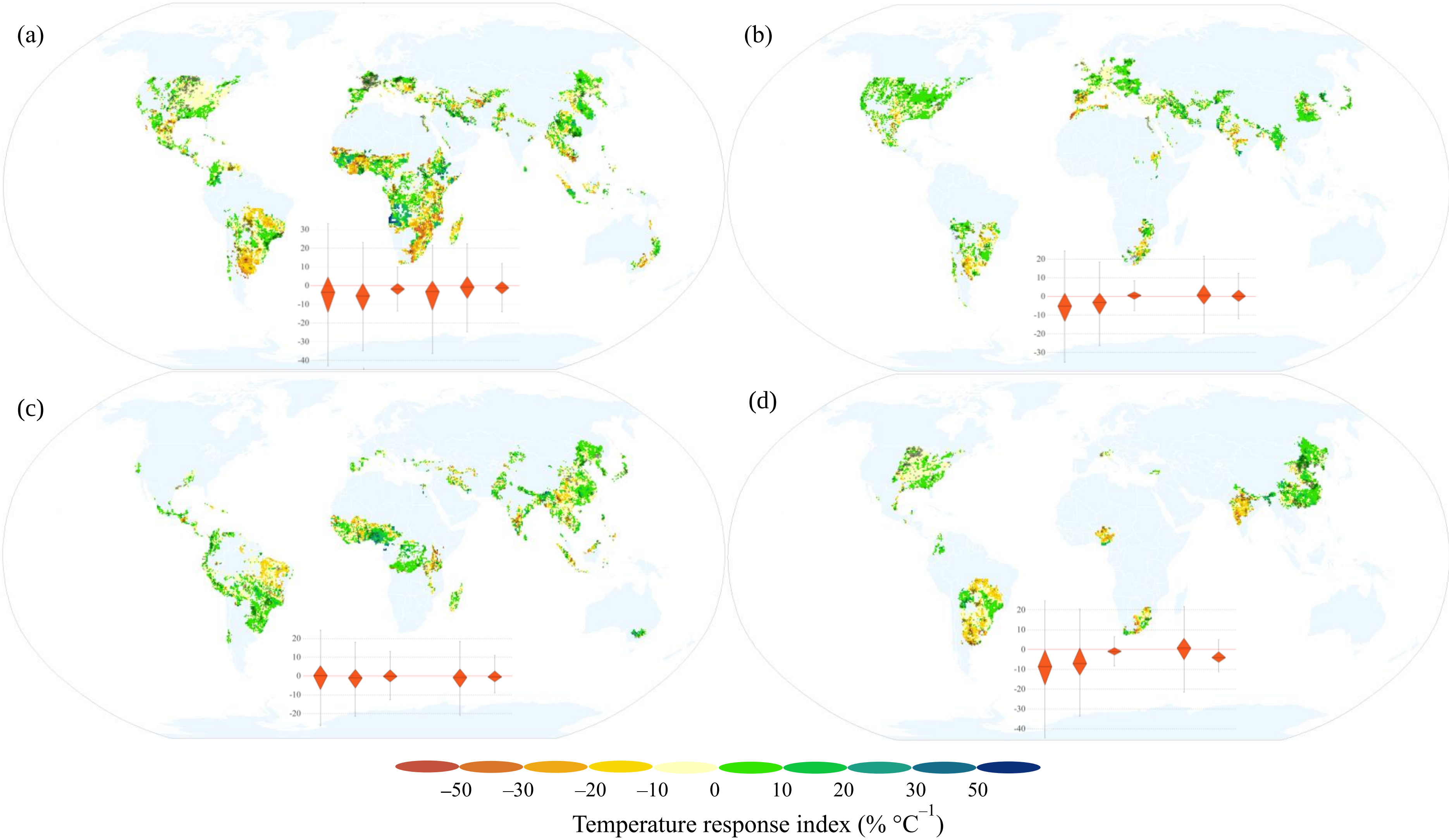
This study provides a soil-focused perspective to address escalating climate challenges on global agriculture, and to look for opportunities in soils for future food security. Here, we firstly determined the response of maize, wheat, rice and soybean yields to warming temperature at grid scale, i.e., temperature response index (TRI, % $°C^{-1}$). Then, we identified the role of soil properties (including SOC) in explaining spatially heterogeneous responses of crop yield to warming, by using a machine learning approach. With outcomes from these processes, we finally proposed soil related strategies for securing food production under future climate change scenarios, and further explored the potential impacts on food security.

Results

Climate change impacts on global crop yield

We defined the temperature response index (TRI) as partial yield percentage changes for each degree Celsius (°C^{-1}) increase. By isolating effects of temperate, it can show crop yield response to climate warming, and indicate yield resilience to future warming by crop and location. TRI was computed for maize, wheat, rice and soybean at the grid level (0.5°×0.5°), using global time series datasets. In general, warming has caused global-scale yield loss, with crop-specific and spatially heterogeneous responses at finer scales (Fig. 1). Globally, the estimates for all four crops show negative TRIs, suggesting an average yield loss of –3.4% °C^{-1} (–32.0 to –19.1% °C^{-1}, 95% distribution interval), –2.4% °C^{-1} (–21.2 to –15.0% °C^{-1}), –0.3% °C^{-1} (–22.8 to –17.4% °C^{-1}), and –5.0% °C^{-1} (–25.2 to –14.3% °C^{-1}) for maize, wheat, rice, and soybean, respectively. However, crop- and location-specific TRIs vary significantly.

In particular, the TRIs for maize are consistently negative across five continents, ranking from high to low: Africa (–6.6% °C^{-1}), South America (–6.3% °C^{-1}), North America (–3.4% °C^{-1}), Oceania (–2.8% °C^{-1}) and Europe (–2.2% °C^{-1}). While on average, maize in Asia is less negatively affected by warming, yield loss is still observed in regions including Southeast Asia, Central Asia and Northwest China (Fig. 1a). For wheat, Africa is the most vulnerable continent, with a TRI of –15.5% °C^{-1}, followed by South America (–7.3% °C^{-1}) and Asia (–1.1% °C^{-1}) (Fig. 1b). Rice is least affected by rising temperatures in many regions, with continental scale TRIs closing to zero (Fig. 1c). The highest yield loss for soybean occurred in South America (–9.8% °C^{-1}), the largest soybean producer, followed by Africa (–8.7% °C^{-1}). The lowest yield loss (–1.4% °C^{-1}) appeared in North America (Fig. 1d). In general, crop production in Africa and South America is more susceptible to warming.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Temperature response index (% °C^{-1})

Fig. 1. Global temperature response indices (TRIs, % °C^{-1}) of four crops. (a) Maize (n=14134), (b) wheat (n=8406), (c) rice (n=9048) and (d) soybean (n=5996). TRI values show yield changes per °C of temperature increase, with positive and negative values indicating yield gain and loss, respectively. The black marks in the grids represent the significant influence of warming. The box chart reflects the interquartile range and the middle line in the box represents the median. The boxes from left to right represent Africa, South America, North America, Oceania, Asia and Europe, and the blank indicates insufficient data in Oceania (b-d).

The role of soil in reducing climate impacts on yield

The spatially heterogeneous response of crop yield to warming can largely be explained by soil heterogeneity in terms of soil properties, including SOC, total nitrogen (NT), clay and sand content, pH and cation exchange capacity (CEC). A random forest technique, based on the concept of bagging sampling and regression decision trees[27], was used to detect soil and spatial TRI relationship (Methods). After training and testing, the random forest model can replicate the crop-specific yields to soil with the coefficient of determination (R^2) of 0.46 to 0.66 (Supplementary Fig. 1), and the relationships can be visualized by centered individual conditional expectation (c-ICE) plot (Fig. 2). c-ICE plot can highlight the average change (colored curves) and variation range (corresponding shadows) of TRI along with soil properties (Fig. 2a–f), and also identify where, and to what extent, heterogeneities might exist[28]. Among six soil properties that potentially affect crop growth, SOC is identified as the most important predictor to TRI, followed by TN, considering the variable importance metric (Fig. 2g). Other soil properties do not affect TRI consistently across the whole range (Fig. 2c-g). This implies that, with increased SOC or TN (except maize) in locations where their current levels are relatively low, TRI could be improved, suggesting increased yield resilience to warming (e.g., Fig. 2a-b). In particular, with increasing SOC, the TRI of four crops would increase until reaching a "plateau" (Fig. 2a). When the SOC is lower than about 2.0%, increasing SOC can considerably reduce TRI, indicating improved yield resilience to warming. Considering current low levels of SOC (Supplementary Fig. 2), global soils have great potential to increase carbon content before reaching the TRI "plateau" level. Current soil TN content, however, has already reached the "plateau" level in most of the planting regions (Supplementary Fig. 3), leaving limited room for improving TRI via TN change. Therefore, in this study, we further quantify spatial TRIs after soil improvement, specifically SOC increase, with associated TN change to maintain soil C:N (Methods).

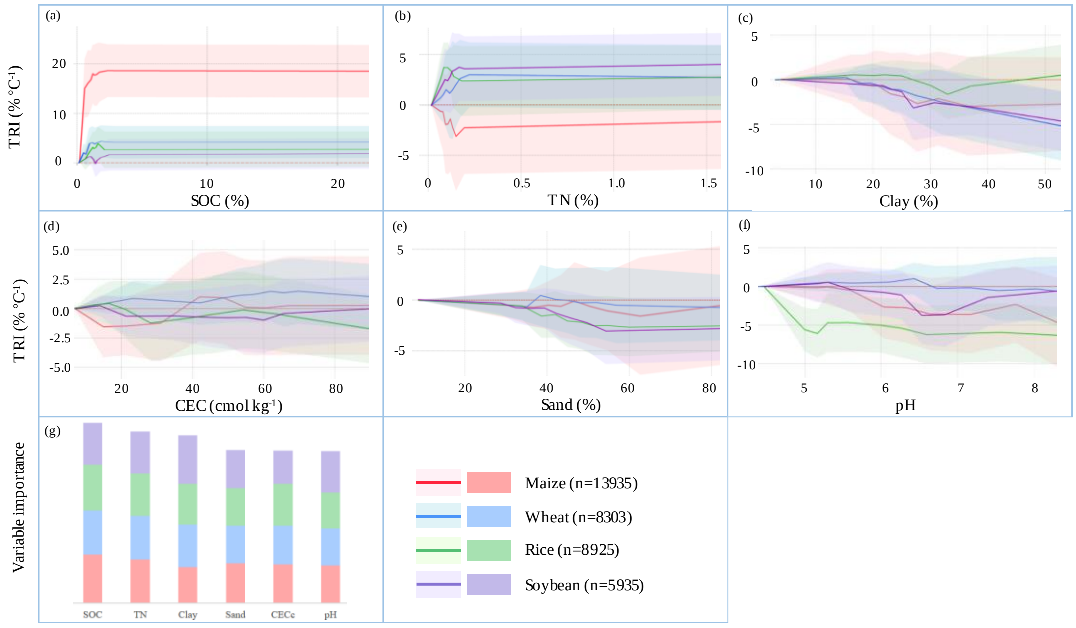


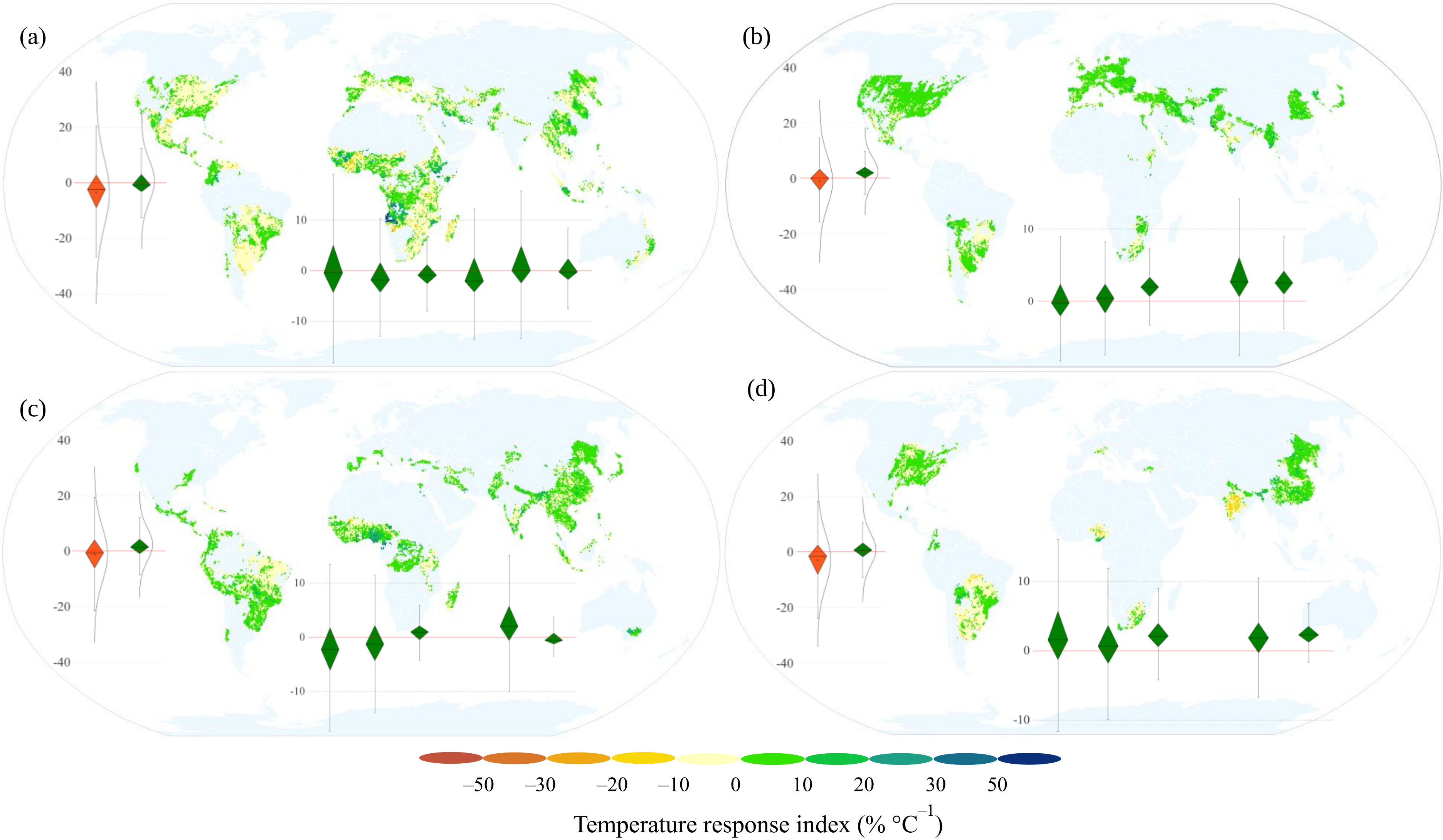
Fig. 2. The temperature response indices (TRIs) vary with soil properties. a–f, centered individual conditional expectation (c-ICE) plot of TRI by six soil properties. Red, blue, green and purple lines represent the averaged TRI changes of maize, wheat, rice and soybean, respectively, with shadow indicating the distribution of all individual instances, relative to the starting point fixed at zero. **g**, the importance of soil properties, sorted from high to low according to the model outputs.

Our analysis shows that improving soil can generally lead to less negative or more positive TRIs (Fig. 3), relative to those with existing soil conditions (Fig. 1). SOC can be sequestered in croplands, depending on biomass and manure inputs, and other management practices, but with an upper limit[29,30]. By considering a "medium" sequestration scenario that SOC increase rate would achieve 26% of the "4p1000" target[31,32], the SOC level can be increased by an average of 1.3% in the study areas

(Supplementary Fig. 2). The considerable SOC increase would mostly occur in Europe (2.6%), North America (2.4%) and Asia (1.6%), where soil carbon loss hotspots are located[33]. With the increase of SOC, the warming-induced yield losses could be significantly reduced (Fig. 3). From a global perspective, the TRIs for maize, wheat, rice and soybean would be 0.1% °C^{-1} (–10.4 to 18.8% °C^{-1}), 2.7% °C^{-1} (–4.5 to 15.0% °C^{-1}), 3.4% °C^{-1} (–6.7 to 17.4% °C^{-1}) and –0.6% °C^{-1} (–11.2 to 14.2% °C^{-1}), respectively. With improved yield resilience owing to soil improvement, about 3.3%-5.1% °C^{-1} of yield loss can be avoided relative to the scenarios without soil improvement.

For maize, in the United States, the largest maize producer, the average TRI would change from –3.7% °C^{-1} to –1.5% °C^{-1}, about 60% of warming-induced yield loss could be avoided (Fig. 3a). In West Africa and East Africa, where yield has reduced by more than 30% °C^{-1} in some areas (Fig. 1a), most of the loss decreased to less than –10% °C^{-1} after improving SOC (Fig. 3a). As for wheat, in both China and India, two of the largest producers, the yield has suffered from different degree of loss due to warming, about –0.1% °C^{-1} and –7.0% °C^{-1}, respectively. With improved soil, the TRIs turns positive in both countries (3.9% °C^{-1} in China, and 1.1% °C^{-1} in India), suggesting potential yield benefit with warming regardless of possible effects from other factors. It is not unexpected that rice is less affected by warming as an irrigated crop, it also benefits from SOC improvement. In particular, for China and India, the top two rice producers, the average TRIs would increase from 1.0% °C^{-1} and 0.3% °C^{-1} to 3.5% °C^{-1} and 4.7% °C^{-1}, respectively, showing even stronger yield resilience to warming. For soybean, its high vulnerability to warming would also be significantly reduced, especially in the main producing countries, Brazil, Argentina and India (Fig. 3d). The SOC strategy would reduce soybean yield loss by 6.4% °C^{-1} in South America (Fig. 3d).

Globally, 53.2%, 67.8%, 51.8% and 71.6% of planting area for maize, wheat, rice and soybean, respectively, could benefit from improved crop resilience due to increased SOC, covering 60.0% of global total planting area (Fig. 1, 3 and Supplementary Fig. 4). Among these area, 77.1%, 95.9%, 90.2% and 88.3% of maize, wheat, rice and soybean, respectively, have experienced yield loss due to warming (i.e., TRI<0). For most of the cropland that have already benefited from warming, i.e., with original TRI>0, SOC improvement has only minimum effect on yield resilience, especially for wheat and rice.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Temperature response index (% °C^{-1})

Fig. 3. The estimated global TRIs (% °C^{-1}) of four crops with SOC improvement. (a) maize, (b) wheat, (c) rice and (d) soybean. The box plots and the curve on the left show the frequency distribution of TRI at global scale. Orange and green boxes represent the overall results without and with SOC improvement, respectively. Green boxes at the bottom show the frequency distribution of TRI of six continents, Africa, South America, North America, Oceania, Asia and Europe, and the blank indicates insufficient data in Oceania (b-d).

Building SOC to secure future food production

Under future climate change, temperature will continue to increase and crop yields are expected to decrease. Over the growing seasons, the average temperature can increase by 0.18-0.21°C, and 1.18-1.44°C in 2050 under RCP 2.6 and RCP 8.5, respectively (Table 1 and Supplementary Fig. 5). Without any improvement to the SOC level, a total of about 15.0 million tonnes of the four crops would be lost in 2050 under RCP 2.6 due to warming (Table 1), leaving 60.0 million people suffering from food insecurity. The loss of production would mainly occur in South America (4.7 million tonnes) and Africa (4.8 million tonnes). The total production loss and the food insecure population would be tripled under RCP 8.5. The largest loss of production can be seen for maize, mainly due to yield loss and relatively large production area (Table 1).

Table 1. Changes in temperature (°C) and warming-induced crop production (million tonnes) in 2050 relative to 2020 level under two climate scenarios.

Crops	Temperature increase		Production change without SOC improvement		Production change with SOC improvement	
	RCP 2.6	RCP 8.5	RCP 2.6	RCP 8.5	RCP 2.6	RCP 8.5
Maize	0.19 (±0.12)	1.42 (±0.31)	–7.5 (±4.6)	–45.7 (±10.1)	–1.4 (±0.9)	1.3 (±0.3)
Wheat	0.21 (±0.06)	1.44 (±0.17)	–3.5 (±1.1)	–13.9(±1.6)	3.2 (±1.0)	31.7(±3.7)
Rice	0.18 (±0.04)	1.18 (±0.24)	–0.2 (±0.0)	–2.9 (±0.6)	5.0 (±1.0)	30.3 (±6.2)
Soybean	0.20 (±0.12)	1.39 (±0.27)	–3.8 (±2.3)	–26.7 (±5.1)	–0.5 (±0.3)	–2.9 (±0.6)
Total	0.20 (±0.06)	1.36 (±0.20)	–15.0 (±4.8)	–89.3 (±13.2)	6.4 (±2.0)	60.4 (±8.9)

However, our analysis showed that with improved yield resilience due to SOC improvement, the warming-induced yield loss can be largely minimized or even reversed. Compared with current SOC levels, improving soil could increase total production of maize, wheat, rice and soybean by 0.6%-1.0% under RCP 2.6, and 4.3%-6.7% under RCP 8.5 in 2050, which would significantly reduce yield loss for maize and soybean, and lead to a global net yield gain for wheat and rice, relative to the reference scenario without SOC improvement. The global production of these four crops would increase by 6.4-60.4 million tonnes, depending on the climate scenario (Table 1). With global efforts to enrich soil carbon, food systems are predicted to provide additional 49.9, 99.7 and 149.6 million tonnes of food that would otherwise lost due to warming, which would be enough to feed an additional 187.9, 375.8, and 563.7 million people in 2030, 2040 and 2050 under RCP 8.5, respectively (Fig. 4). Asia would benefit the most from SOC improvement. An additional 78.5, 157.0 and 235.5 million people could be fed in 2030, 2040 and 2050 under RCP8.5, respectively (Fig. 4). Among the four crops in Asia, wheat and rice contribute more than 90% to the increase of food production. In Africa, an additional 21.2, 42.4 and 63.6 million people are expected to avoid hunger in 2030, 2040 and 2050 under RCP8.5, respectively, mainly due to the contribution of maize (Fig. 4). Other areas would also benefit from improved yield resilience owing to increased soil carbon content (Fig. 4).

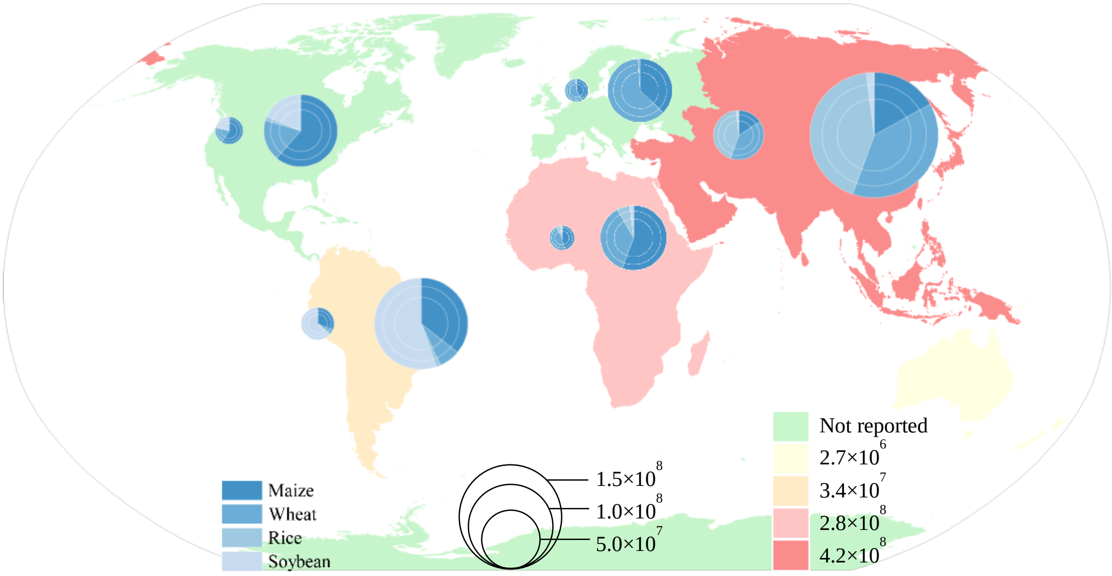

Fig. 4. Increased food secure population (people) with improved soil. The results are aggregated by continents. A pair of pies in each continent correspond to RCP 8.5 (left) and RCP 2.6 (right) climate scenarios. Pies from the inside out indicate the results in 2030, 2040 and 2050, and the area of the pie represents the predicted size of increased food secure population. The background map shows the number of people undernourished in 2020[1]. The undernourished people consume calories below the minimum energy requirement for an active and healthy life, and food secure population indicates that an individual's dietary calorie requirements are fully met.

Discussion

This study specifically investigated partial crop yield response to warming by excluding other factors (e.g., precipitation, crop variety, management), showing relatively comparable findings with other relevant studies. Globally, rising temperature caused maize, wheat and soybean yield losses on average, but with spatial divergence (Fig. 1). For instance, crop in high-latitude regions would benefit from climate warming due to the relief of chilling[34]. Rice yield was less affected by rising temperature compared with the other three major crops, consisted with previous meta-analyses and statistical modeling[5,13]. More irrigated area of rice in the main producing country may bridge the water deficit associated with warming[35]. Note that the yield loss per °C of global average warming for maize and wheat was smaller than that found in previous studies[5,6]. A major reason is that we further isolated the effects of nitrogen and phosphate fertilizer application. Fertilizer additions can meet higher nutrient requirements of crops under climate change[36,37]. With SOC improvement, the yield losses due to warming are predicted to be reduced or even reversed, and therefore the food demands of tens to hundreds of millions of people worldwide would be met.

While there have been studies investigating the relationships between crop yield and climate factors, there has been a lack of field evidence to isolate the role of soil in building yield resilience to climate warming[16]. However, some existing understanding and evidence can still imply the importance of soil system. A recent report from on-farm trials in China suggests that high-quality soils can reduce the sensitivity of crop yield to climate variability and stabilize crop yield[16]. Compared with soils of low quality, high-quality soils are proven to improve yield under climate change by an average of 1.7%[16]. This study provides field evidence to our findings at the global scale that soil improvement can increase resilience of the soil-crop system to climate change (i.e., soil resilience, crop resilience and resilience of the integrated system) and help secure future crop production. Globally, the benefits of increased SOC are particularly pronounced in wheat cropping systems (Table 1), and this negative-to-positive effects of improved soil on yield also appeared in regional cases[16]. More importantly, our study indicates that for regions that are more susceptible to warming, increasing SOC would lead to greater yield resilience. For instance, in Africa that has the highest prevalence of undernourishment (19% in 2018-2020)[1], the TRI of maize and soybean can be increased by ~7% $°C^{-1}$ with SOC improvement, doubling the global average. In these warmer and less irrigated areas, increasing SOC would prominently alleviate the heat stress on crops (Supplementary Fig. 4, 6). However, SOC above 2% would not result in additional benefits to crop yields (Fig. 2). The threshold effects of SOC was also detected in field experiments[24]. Currently, SOC content is below 1.5% in two-thirds of planting grids (Supplementary Fig. 2), which leaves great potential to stabilize crop yield under warming by improving SOC.

Notably, the mechanisms by which improved soil reduces the climate impact on crops are not fully known. Soil health management by increasing SOC can increase crop resilience under extreme climate stress[22,26,38], which is likely to ensure food security under climate change at regional and global scales. Specifically, SOC underpins soil structure, soil formation, water cycling and nutrient cycling[20]. Poor soil structure (e.g., soil compaction) lowers root biomass. Increasing SOC concentration could therefore increase the porosity across different soil textures[39], which promotes root growth, and nutrient and water uptake of crops under climate change[40]. Increased organic matter can increase soil water holding capacity, thereby alleviating the damage of heat and drought and increasing resilience of maize[41]. The crop is less sensitive to heat in medium- and fine- textured and carbon rich soils, partially due to restricted water loss through evapotranspiration[42]. In this study, compared with wheat and soybean, maize and rice would benefit less from improving SOC, probably because maize as C4 plant has smaller stomatal conductance to concentrate CO_2[43,44], and rice are often irrigated and less water-stressed. Field experiment showed that rice could benefit from a higher temperature when soil nutrients keep up with the demand[36]. Given that higher crop biomass returns more C into soil[45], the interaction between yield and SOC increase presents a positive feedback[24]. SOC and TN losses, which were pre-simulated by the process-based model under a 3°C warming, would reduce wheat yield by 13% and maize yield by 19%[46]. However, few studies have achieved timely feedback on the interaction between crop yield resilience and soil properties, primarily because multiple factors and complex processes are involved, and the role of soil cannot easily be isolated in the overall yield resilience observation. It is expected that the relationship between TRI and soil might be revealed if paired warming experiments could include diverse crop-soil-environment conditions.

It should also be noted that the ability of building SOC to improve yield resilience may be limited in certain regions (Supplementary Fig. 4), and management practices should be well examined. Due to the increase of soil water retention, the negative effects of increasing SOC on maize, wheat and soybean may occur in wet regions with poorer drainage[42]. The increase of SOC significantly increases the specific heat capacity of the soil[47], which causes soil to warm slowly during the wheat rejuvenation period[42]. The areas with greater benefits after improving SOC could be given higher priority in regional or national planning (Fig. 1, 3 and Supplementary Fig. 4). For areas with higher poverty and undernourishment, smallholders may not be able to afford costly measures[48], so effective economic and policy incentives would need to be in place[25,49]. Food security and other benefits, including ecosystem service and negative emissions[50,51], can further justify government investment. Fast and effective action is required globally[52,53].

Soil management should also well reflect the level of confidence in both science and practice. The potential SOC in our study considered the management scenario with cover cropping, manure application and conservation tillage, it would be higher than the potential based on the meta-analysis with applicable constraints[54]. Compared with "4p1000" initiative, potential SOC was simulated with a relatively conservative sequestration rate, reaching only 26% of the "4p1000" target[31]. SOC losses due to warming was not specifically considered in this estimation. Regarding the regional sequestration potential, long-standing cropping regions in Europe, North America and Asia show higher rate (Supplementary Fig. 2), which is associated with large carbon losses due to intensive land use, leaving more room for carbon accumulation[33,55]. From a technical perspective, increasing organic inputs (e.g., crop residue, cover crop and manure) is considered as the most effective measure to accumulate SOC in cropland[56,57]. Crop residue return is a feasible and efficient way to increase SOC density by 0.69 Mg C ha^{-1} yr^{-1} under a high retention rate[45]. Irrigation of arid and semiarid regions may increase SOC through increase biomass production[58]. Optimal agricultural management in China is estimated to sequester 2.4 Pg C into cropland before 2050, with higher potential for paddy soil (26.1 Mg C ha^{-1})[29,59]. Notably, soil N_2O and CH_4 emissions may change as a result of management improvement, which should be further studied and well balanced in estimating crop yield and climate benefits[60,61].

Future work is urgently required to further improve yield resilience and future yield estimation, and investigate potential unintended consequences. Modeling uncertainties may arise from data limitation, choice of GHG emission scenarios, climate model projections and understanding of mechanisms. For instance, although precipitation change was included in our modeling analysis, no significant trends were detected. The lack of irrigation in the model, due to data limitation, may have partially missed the water impacts. If crop-specific irrigation data with high spatio-temporal resolution become available, the cooling and water supply effects of irrigation could be better modeled[62,63]. Spatially referenced and crop-specific data on fertilization, if become available, could also help improve model simulations. Additionally, since TRI is a simplification of the actual response of crop to temperature change, future studies could further include biophysical processes to better understand crop-soil-environment interactions[20]. Furthermore, socioeconomic drivers of food supply and demand besides domestic production of crops, e.g. trade[64], are important to assess the hunger and food secure population. Finally, acting on soil may lead to other unintended negative environmental (e.g., water, nutrients input), social (e.g., competitive use of resources) and even economic outcomes (e.g., shift of investment), and these should be avoided to the greatest extent possible[65-67]. Given the multiple benefits of building SOC, the priority should be given to take efficient management steps considering the integrated crop-soil-environment system to close the yield gap and ensure the security of food supply.

Methods

Yield response to temperature. On the basis of historical data reflecting crop yields, climate and management, the yield models (Eq. 1) were developed for individual crops (i.e., maize, wheat, rice, and soybean), and then used to identify yield's partial response to temperature (i.e., TRIs or temperature response indices, Eq. 2). Historical yields (1981−2010) of main crops, maize (major), wheat (winter), rice (major) and soybean with the spatial resolution of 0.5°, were derived from GDHY v1.3, a global dataset of historical yields of major crops with a data combination of agricultural census, satellite and model[68]. Historical daily weather data were sourced from the AgMERRA, a post-processing dataset of the NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA) for agricultural modeling[69]. Average temperature (T), total precipitation (P) and solar radiation (R) of crop growing season were extracted according to phenology of each crop[70]. Both linear and quadratic forms of temperature and precipitation were characterized in the model to account for the non-linear response of crop yields to climate (Eq. 1). The model has been widely applied in the studies of yield-climate relationship[5,71,72], and fully verified[73,74]. Nitrogen ($Nfer$) and phosphorus ($Pfer$) fertilizers[75] were further included to better estimate the impacts of management on crop yields. The input datasets with higher resolution were integrated to 0.5°, to be consistent with the resolution of yields (Supplementary Table 1). The model structure is shown as:

$$\ln\left(Y_{i,t}\right) = \beta_{0,i} + \beta_{1,i}t + \beta_{2,i}T_{i,t} + \beta_{3,i}T_{i,t}^{2} + \beta_{4,i}P_{i,t} + \beta_{5,i}P_{i,t}^{2} + \beta_{6,i}R_{i,t} + \beta_{7,i}Nfer_{i,t} + \beta_{8,i}Pfer_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $\ln(Y_{i,t})$ represents the logarithm of crop yields. Models of four crops were developed for grid cell i (0.5°×0.5°). The time term (t) was used to simulate the possible impact of other factors on crop yields (Supplementary Fig. 7), e.g. cultivar shifts. As showed in this study (Supplementary Fig. 8) and elsewhere[5,76], including the quadratic form (e.g., T^2) can better simulate the nonlinear responses of the crop to warming. The response of crop yield to temperature was measured by the partial derivative of equation (1)[76]:

$$\partial \ln(Y_i)/\partial T_i = \partial Y_i/(Y_i \times \partial T_i) = \beta_{2,i} + 2\beta_{3,i} T_i \quad (2)$$

where $\partial Y_i/Y_i$ represents the proportion of yield change in grid cell i. Temperature response index (TRI_i) was defined as the yield change (%) per °C of temperature change, which can be measured as[77]:

$$TRI_i \approx (\beta_{2,i} + 2\beta_{3,i} \overline{T}_i) \times 100\% \quad (3)$$

where $\overline{T}_i$ is the average temperature of the crop growing season during 1981–2010. The parameters $\beta_{2,i}$ and $\beta_{3,i}$ represent the location-specific response of yield to temperature change. *TRI* varies spatially, with values determined by grid level parameters and local climate. The *TRI* at the continental and global scales was calculated on the basis of the area-weighted average, considering geographic distribution of crop harvest area derived from a gridded dataset[78]. Modeling and analysis were batched in Python version 3.6.

Estimation of the role of soils. Soil plays a crucial role in providing nutrients, maintaining relatively stable environment, and supporting crop growth as a whole[24,26]. We hypothesized that the spatial heterogeneity of TRI correlates to the differences of soil properties across space. The machine learning approach, random forest[27], was employed to estimate the correlation between *TRI* and soil properties due to its efficient modeling performance. WISE30sec dataset[79] was selected for its comprehensive soil properties and data sources. Six key soil properties (0–30 cm), SOC (%), total nitrogen (TN, %), cation exchange capacity (CEC, cmol kg^{-1}), clay content (%), sand content (%), and pH were extracted by depth-weighted method and resampled to 0.5° resolution. Random forest models were built for individual crops, maize (n=13935), wheat (n=8303), rice (n=8925) and soybean (n=5935). Model training and testing were implemented with the Scikit-learn Library in the Python. Three key parameters needed to be adjusted for training the models, the number of trees in the forest (*n_estimators*), the maximum depth of the tree (*max_depth*) and the number of soil variables in the random subset at each node (*max_features*), for the trade-off between over-fitting and high bias of the model. When training, all decision trees in the forest were formed by the method of bagging sampling with replacement. In each training set, about one third of samples were left out as out-of-bag data, which were then used to estimate the generalization error.

The key soil properties were determined by the importance and the interaction between *TRI* and each soil variable. The former was measured by calculating the increase of prediction error after randomly permuting the target soil variables in the random forest model. The greater the increase in error, the more important the variable is. The latter was visualized by centered individual conditional expectation (c-ICE) plot[28]. The curve in the plot showed how the *TRI* changes when a soil variable changed after considering the average effects of other variables. All individual samples were centered at a certain point in the plot, which was helpful in examining the cumulative effect of the selected feature. Besides, the c-ICE plot visualized the condition of each individual sample (shaded areas on both sides of the curve, Fig. 2).

Through these analysis, SOC content was determined to be the most important soil factor affecting crop response to temperature change, followed by TN. For global soil, a linear relationship was observed between SOC and TN (R^2=0.91), and this was further built into the equation to estimate future TRI with improved SOC. In other words, the improved yield resilience would be realized by feeding in SOC potential and associated TN change. Specifically, SOC potential was based on the field-supported assumption that best management could help soil carbon accumulation and reach a relatively high and stable SOC level[54]. In this analysis, SOC data from Zomer, et al. [31] was used for its global-scale availability and accuracy. The medium scenario was considered here with the sequestration rate of 0.56 t C ha^{-1} yr^{-1} (0.9 Pg C yr^{-1} globally) lasting at least 20 years[31], by implementing practices including cover cropping, manure application, and reduced tillage. The unit (%) and resolution (0.5°) of SOC data were converted and integrated to match the random forest model. The average TN content modeled through the linear model was 0.19% (0.07-0.49%, 95% percentile).

Crop yields under future climate. With the changing temperature in the future, crop yield would respond differently among crops following individual TRI pattern. The highest and lowest additional radiative forcing scenarios (RCP2.6 and RCP8.5), 2.6 and 8.5 W m^{-2}, respectively, were considered for future climate scenarios[80,81]. The monthly temperatures of two scenarios were obtained from the outputs of Global climate models (GCMs) in CMIP6. According to the latest comparison of the equilibrium climate sensitivity (ECS)[82], we chose three GCMs with lowest ECS from different institutes, including INM-CM5-0, CAMS-CSM1-0 and NorESM2-MM. In order to be spatially consistent with other data, we aggregated the temperature data of above GCMs to a 0.5° resolution. We averaged all model outputs for a relatively stable and accurate temperature projection. According to the phenology data of maize, wheat, rice and soybean, we extracted growing season temperature between planting and harvest date. Warming trends of crops in growing season were detected by linearly fitting the temperature from 2015 to 2100 in each grid. Then, we calculated the warming level in 2030, 2040 and 2050 relative to 2020 by using the above parameter of trends. The future crop yield changes as a result of yield response and future warming.

Estimation of increased feed. Future production under changing climate varies with SOC strategies (i.e., with vs. without SOC improvement), which would lead to different estimates of food secure population (FSP) that could be met with full dietary calorie requirements. The production was determined by yield depending on crop-specific TRI, and harvest area simulated under future climate[83]. The *FSP* was calculated as follows:

$$FSP_{c,j,t} = TRI_{c,j} \times \Delta T_{c,j,t} \times Y_{c,j} \times H_{c,j} \times CC_j \,/\, PC_{c,t} \qquad (4)$$

where $TRI_{c,j,t}$ indicates the temperature response index of continent c, crop j and year t. $\Delta T_{c,j,t}$ is the temperature change of the crop growing season under two climate scenarios compared to current level. $Y_{c,j}$ and $H_{c,j}$ represent the yield and harvest area[83], which were assumed to be constant. Using four variables described above, we calculated the production change due to future warming. CC_j is the calorie content per unit of crop j[84]. $PC_{c,t}$ is the calorie need per capita per year[83], which was simulated under two scenarios, business-as-usual (BAU) and towards sustainability (TSS) scenarios, corresponding to RCP8.5 and RCP2.6, respectively, to be consistent with future climate scenarios. $PC_{c,t}$ of two scenarios was estimated based on the different forward-looking assumptions, e.g., economic growth and policy[83]. The $FSP_{c,j,t}$ with and without SOC strategy was estimated with their corresponding $TRI_{i,j,t}$. The *FSP*, and increased food secure population (ΔFSP, difference between *FSP* with and without SOC strategy) were estimated for year *t* (i.e., 2030, 2040 and 2050).

Data availability

All the source data of this study are freely available online and referenced within the paper. The summary of the dataset is included in the Supplementary Information.

Code availability

The code used to perform analyses in this study is generated in Python36 and is available upon reasonable request.

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Author contributions

Z. Q. and Y. H. conceived and designed the research. X. D. and Z. Q. developed data-model simulations and analyzed results, with key inputs from Y. H., W. Y. and W. Z. on model improvement. P. C., W. D. and P. S. helped with interpretation of the results and discussion. X. D., Y. H. and Z. Q. wrote the manuscript with contributions from all authors.

Competing interests

The authors declare no competing interests.