Effect of a behaviour change intervention on household food hygiene practices in rural Bangladesh: A cluster-randomised controlled trial

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Temperature thresholds of extreme heat-induced yield loss in maize and soybean reveal geographic heterogeneity across the Northern Hemisphere

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Extreme heat is a widely recognized threat to global food security[1]. It accelerates premature crop senescence, damages photosynthetic organs and causes yield losses[2–6]. Recent estimates suggested that extreme heat events account for around 10% of annual global cereal pro-duction losses globally[7], equivalent to over 1 month's requirements for the global population. The increasing frequency of extreme heat events in breadbasket regions further destabilize global food production[8,9], increasing the risk of food price spikes[10] and exacerbating hunger[11]. When assessing the extreme heat impacts, crop-specific temperature thresholds that define the onset of harmful extreme heat exposure have been widely used at large scale[3,6,12,13], implicitly assuming the thresholds are spatially constant within a given crop. The extreme heat exposure actually experienced by crops, however, could vary spatially as heat impacts are not only shaped by genotypes[14,15] but also by environmental conditions[16–18] and agronomic management (for example irrigation[19–21], which could raise the threshold by ~5 °C (ref. 22)). These drivers differ from region to region, implying pronounced geographic heterogeneity in exposure. Under rapid global warming, the occurrence of high temperature is projected to increase[23], which will expose crops to more heat events and further negatively affect food productivity[8,9,24]. The absence of spatially resolved extreme heat threshold constitutes a fundamental limitation in climate vulnerability assessments, hindering better prediction of yield losses under future warming.

Numerous studies have provided evidence that extreme degree days (EDDs)[3,6,25] serve as an effective metric for quantifying the impact of heat stress on crop yields. EDDs are calculated by summing air temperatures that exceed a specific temperature threshold, thus capturing the severity of extreme heat exposure. Consequently, the choice of this threshold (EDDthreshold) is critical for assessing extreme heat-related risks during the growing season. Above the EDDthreshold, the exposure to high temperatures results in yield decline substantially[2]. However, most cur-rent studies just applied a fixed temperature value across large regions, overlooking spatial variations on the EDDthreshold.

Whereas some studies set the threshold for maize and soybean around 40 °C (refs. 12,13,26), in others, heat stress may already arise below 30 °C (refs. 9,27,28), leading to inconsistencies in estimating extreme heat exposure.

Here we harmonized yield records over nearly 8,000 districts or counties to provide an estimation on the EDDthreshold for maize and soybean at fine spatial scale across major breadbasket regions of the Northern Hemisphere. Our study regions generally supply two-thirds of global maize production and half of global soybean production (Fig. 1a,b). With our new estimated EDDthreshold, we then projected future change in extreme heat exposure for maize and soybean based on outputs from 11 global gridded crop models (GGCMs). We also evaluated the potential difference of the projected extreme heat expo-sure that arises from using widely applied spatially fixed threshold (30 °C (refs. 2,3,29,30)) with our EDDthreshold. Finally, we assessed how growing-season adaptations by advanced sowing dates and adoption of long-maturity cultivars may help crops to escape extreme heat exposure.

Estimation of the EDDthreshold in the Northern Hemisphere

Using detailed county-level yield datasets from major producing regions in the Northern Hemisphere, we derived the spatial pattern of EDDthreshold for maize and soybean (Fig. 1c–f). The average (± stand-ard deviation) EDDthreshold for maize was 34.8 ± 4.0 °C (median: 35.0 °C; interquartile range (IQR) equals: 31.2 °C to 38.4 °C), while for soybean was 33.7 ± 3.9 °C (median: 35.0°C; interquartile range (IQR) equals: 31.4 °C to 38.8 °C), respectively (Fig. 1c–f). Both crops showed strong spatial heterogeneity. Higher EDDthreshold for maize was found in South Europe, northwestern China and midwestern USA, whereas higher soybean thresholds were detected mainly in the North China Plain and central USA (Fig. 1c,d).

We verified the robustness of EDDthreshold for both crops under mul-tiple methodological assumptions, grouped by three types: regression structure modifications, climate data-source alternatives and growth stage definition adjustments (Methods and Supplementary Figs. 1–12). Our results revealed that first, the distribution of EDDthreshold remained nearly unchanged when altering the parameters of base temperature (Supplementary Figs. 1 and 2). Second, different model structures on the interpretation of growing degree days (GDDs), yield detrending, proxies of water availability, the consideration of other explanatory variables and different choices on climate datasets resulted in minimal differences, while the EDDthreshold estimates in majority regions were significantly correlated and similarly distributed (Supplementary Figs. 3–11). Third, even when isolating the critical stage of anthesis and grain filling (AGF) from the growing season, a period expected to amplify sensitivity, only minor differences on EDDthreshold were observed (Supplementary Fig. 12). These tests confirm that our methods are robust in assessing extreme heat exposure that causes yield loss across diverse analytical frameworks.

We further benchmarked our estimates on EDDthreshold against prior experimental and observational studies and found broad consistency with reported thresholds in the observation locations (Supplementary Table 1). These spatial variations were difficult to be explained in these sporadic studies, but our analyses on the pan-Northern Hemisphere pattern showed that climatic factors account for ~30% of the observed variance (Supplementary Figs. 13 and 14, and Supplementary Notes). Management factors, such as irrigation, also had a significant impact on EDDthreshold. In counties where irrigated and rain-fed systems coexisted over midwestern USA, EDDthreshold was significantly higher under irrigated management by approximately 1.1 °C for maize ($P = 0.009$) and 3.5 °C for soybean ($P < 0.001$) (Supplementary Fig. 15).

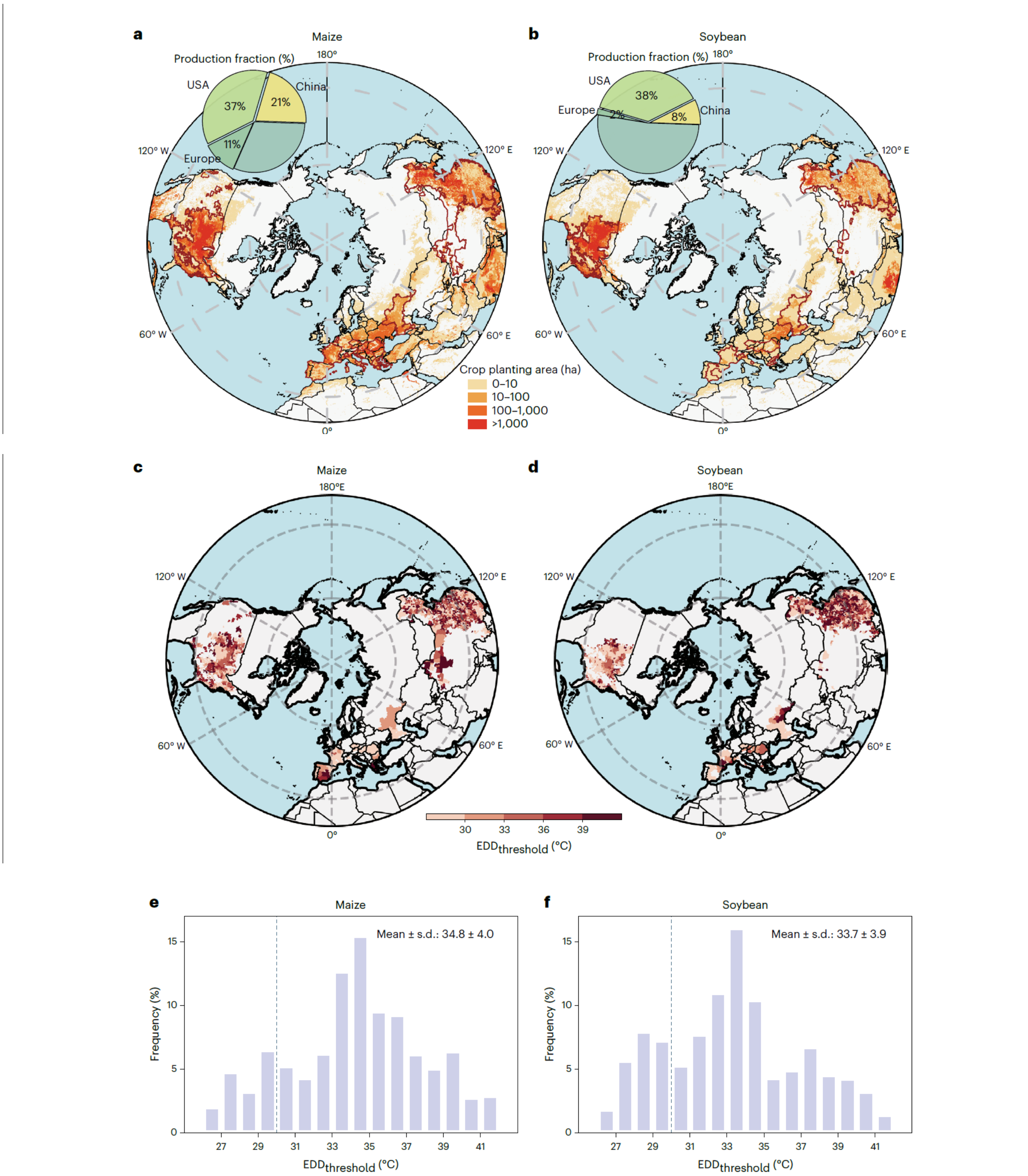

Figure. 1 Spatial patterns of EDDthreshold in major maize and soybean breadbaskets across the mid- to high-latitudinal Northern Hemisphere. a,b, Spatial patterns of planting area for maize (a) and soybean (b) based on Spatial Production Allocation Model (SPAM) (data from ref. 49). The red lines indicate study regions. Insets show the proportion of total global production within the study area (categorized by the USA, China and Europe). Note that only regions with consecutive yield records and detectable threshold (that is, experienced high-temperature exposure in growing season) are included. c,d, Spatial patterns of EDDthreshold for maize (c) and soybean (d). e,f, Histograms of EDDthreshold for maize (e) and soybean (f), weighted by regional plant area. The dashed line represents 30 °C. s.d., standard deviation. Basemap data in a–d from Natural Earth (https:// www.naturalearthdata.com; USA), Eurostat (https://ec.europa.eu/eurostat/web/ gisco/geodata/statistical-units/territorial-units-statistics; EU), Simple Maps (https://simplemaps.com/gis/country/ru; Russia) and the Standard Map Service (https://cloudcenter.tianditu.gov.cn/administrativeDivision; China).

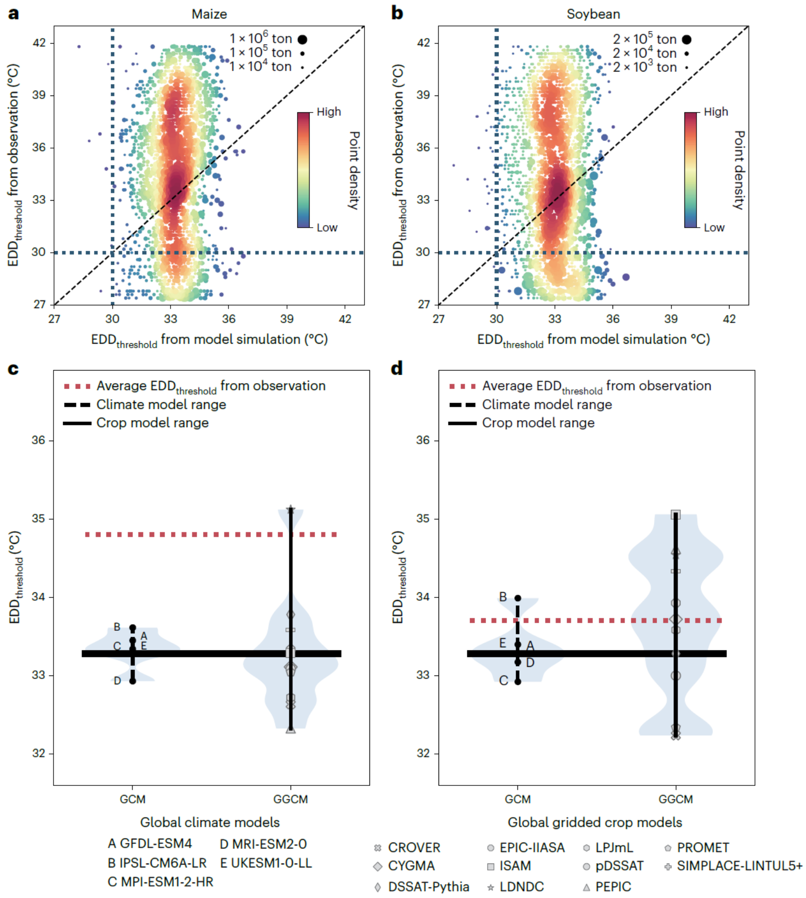

Figure. 2 Comparison with EDDthreshold estimation from process-based crop models. a,b, Scatter plots of EDDthreshold derived from climate and crop models and EDDthreshold derived from observational datasets for maize (a) and soybean (b). Each point represents a subnational geographical unit, with point size indicating average production and colour indicating point density. The black dashed line represents 1:1 line. c,d, The black horizontal lines show average model-derived EDDthreshold for maize (c) and soybean (d), weighted by production. The red dotted lines show the average EDDthreshold value from observation. Whiskers indicate the range of global climate models (GCM, dashed line, as the mean across crop models) and the range of GGCMs (solid line, as the mean across climate models). Individual model results are represented by letters and symbols along the whisker lines. Shaded areas describe the distributions of models.

Projected increase in future extreme heat exposure

Leveraging our spatially explicit EDDthreshold, we found a substantial increase in extreme heat exposure for maize and soybean by mid-century (2041–2060) and towards the end of this century (2081–2100) (Fig. 3a–d and Supplementary Fig. 17). During the baseline period (2000–2019), the observed average extreme heat exposure normalized by growing-season duration were 7.8% (9.8 days) and 9.1% (11.3 days) for maize and soybean, respectively. By the end of the century, even under the low-emissions scenario (Shared Socioeconomic Pathway 1-2.6), these values rise to 10.2% (12.0 days) for maize and 11.9% (13.9 days) for soybean (Fig. 3a–d and Supplementary Fig. 17). In contrast, the high-emissions scenario (SSP5-8.5) leads to far more severe impacts, with extreme heat exposure reaching 24.1% (26.2 days) for maize and 25.3% (26.0 days) for soybean—a nearly threefold increase compared to 2000–2019 levels (Fig. 3a–d and Supplementary Fig. 17).

Importantly, ignoring spatial variations in EDDthreshold by adopting a fixed 30 °C threshold led to systematic overestimation of extreme heat exposure during both hindcast and projection period (Fig. 3e–h and Supplementary Fig. 18). For maize, the fixed threshold overestimated baseline exposure by 3.3% (6.8 days), increasing to 6.2% (12.2 days) under SSP126 and 9.3% (14.9 days) under SSP585 by mid-century. For soybean, the overestimation was 3.4% (8.2 days) for the baseline and projected to be 7.0% (14.8 days, SSP126) and 10.2% (17.9 days, SSP585) by mid-century. This equates to falsely classifying up to 2 weeks of the growing season as heat stressed in key breadbasket regions of North-ern Hemisphere, such as the North China Plain and the US Corn Belt (Fig. 3i–l and Supplementary Fig. 18), which is of particular concern as the misclassification often took place during the AGF stage—the phenological stages when crops are sensitive to thermal variability (Fig. 3), which could partially explain the bias of crop models in assessing impacts of extreme heat events[31].

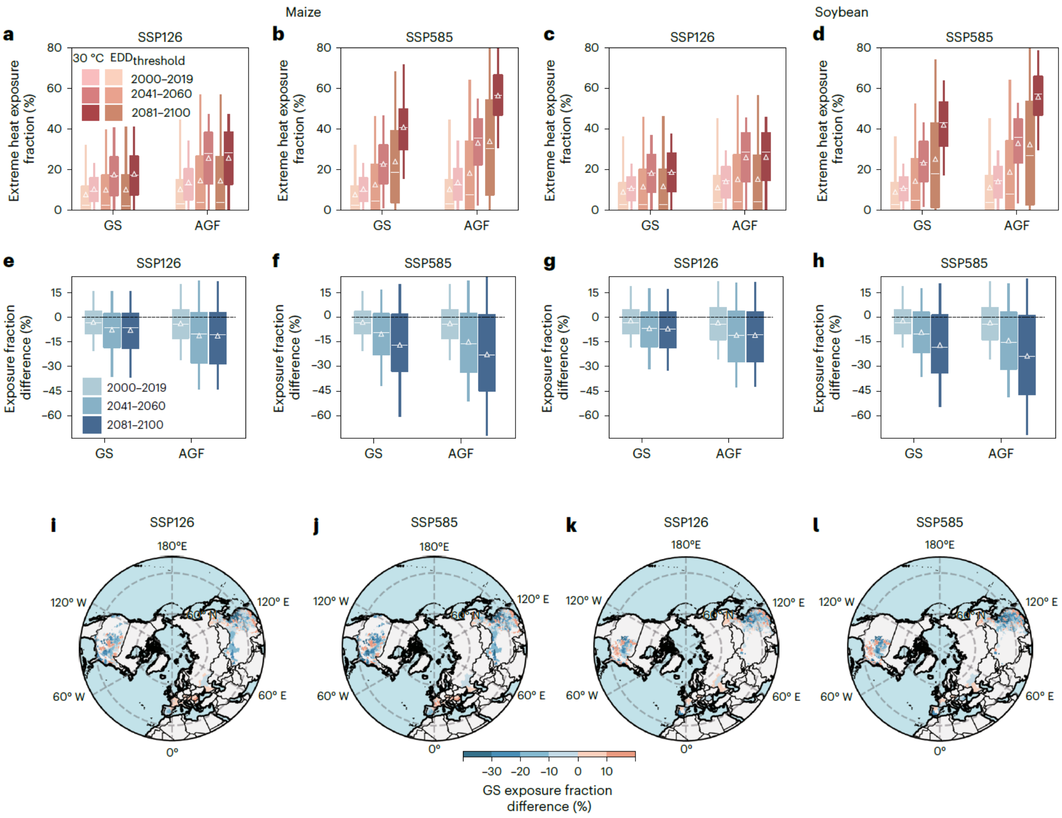

Figure. 3 Projected fractions of extreme heat exposure and differences between EDDthreshold and the prevailing constant threshold for maize and soybean. a–d, The fraction of extreme heat exposure, expressed as a percentage of the length of the growing season, shown as the multi-year average values across climate and crop models for maize (a,b) and soybean (c,d) under SSP126 (a,c) and SSP585 (b,d). e–h, Projected differences (calculated as the difference of extreme heat exposure fraction between by the regional varying EDDthreshold and by fixed 30 °C) in growing season for maize (e,f) and soybean (g,h) under SSP126 (e,g) and SSP585 (f,h). i–l, Spatial patterns of growing-season exposure fraction differences in 2041–2060 for maize (i,j) and soybean (k,l) under SSP126 (i,k) and SSP585 (j,l). The box charts (for maize, n = 3,581; for soybean, n = 3,516) show the distribution of region-specific exposure fraction differences in growing season (GS) and in AGF. Colours ranging from light to dark represent different time periods for historical observation (2000–2019) and future projection (2041–2060 and 2081–2100). The ends of each box and the line inside represent the 25th, median and 75th percentiles, and triangles represent the mean value. Whiskers represent the range of 5th and 95th percentiles. Basemap data in i–l from Natural Earth (https://www.naturalearthdata.com; USA), Eurostat (https://ec.europa.eu/eurostat/web/gisco/geodata/statistical-units/territorial-units-statistics; EU), Simple Maps (https://simplemaps.com/gis/country/ru; Russia) and the Standard Map Service (https://cloudcenter.tianditu.gov.cn/administrativeDivision; China).

Growing-season adaptations cannot fully compensate the increasing extreme heat exposure

Though our estimates show less extreme heat exposure than what would be identified using a fixed threshold of 30 °C, a warmer future would thus cause greater extreme heat exposure without adaptation. To assess whether agronomic adaptation, such as adjusting planting dates or extending the growing season[32,33], might mitigate increasing extreme heat exposure, we examined three adaptation scenarios: (1) adjusting sowing dates, earlier sowing in warmer climates, (2) maintaining a fixed growing-season length[34] and (3) a combination of earlier planting and constant growing-season length (Methods). While these adaptation scenarios reduced overall extreme heat exposure for both crops compared with the no-adaptation scenario, they failed to fully counteract its escalation. The attenuation effect, however, is scenario dependent: the exposure with adaptation would increase by only 1~2% of the growing season under SSP126 (Fig. 4), while increase by at least 4% under SSP585 in mid-century (Fig. 4) and may double at the end of the century (Supplementary Fig. 19). Moreover, the pronounced surge in extreme heat exposure during anthesis cannot be compensated by the warming-induced acceleration of crop developments[34] (Supplementary Fig. 20). This further highlights the urgency of climate-mitigation actions, without which adaptation efforts would fail in containing the increasing risk of extreme climate events.

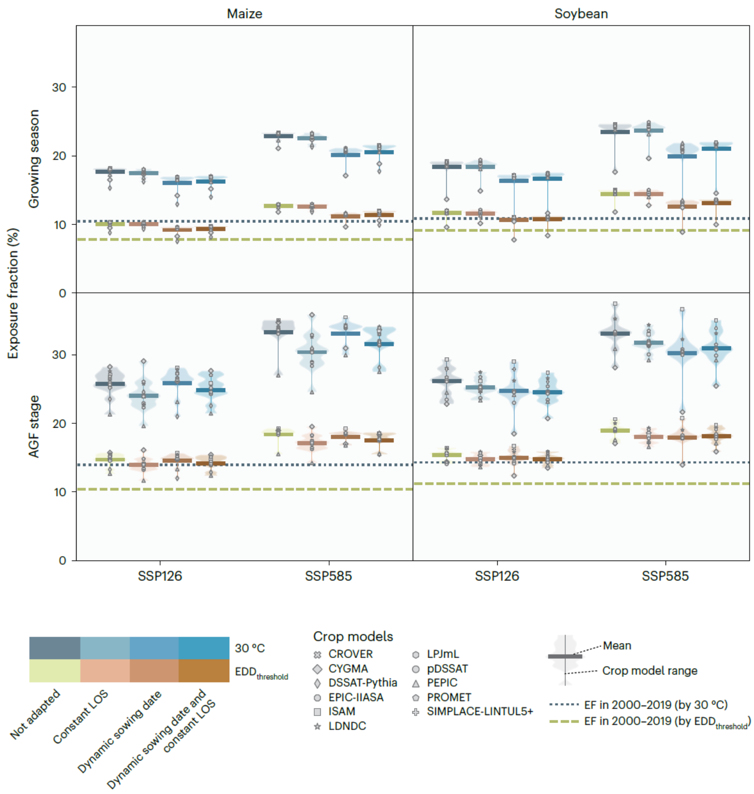

Figure. 4 The effects of growing-season adaptations on exposure to extreme heat for maize and soybean in 2041–2060, SSP126 and SSP585. Projected future exposure fraction for three adapted growing seasons (Methods), and the default growing season in GGCMI crop models are shown using the spatial varying EDDthreshold and the prevailing fixed 30 °C, presented as the average values across models (bold horizontal line). The range of crop models is indicated by the solid vertical lines. Individual model results are denoted by symbols (for maize, n = 11; for soybean, n = 10), and the model distributions are illustrated by shades. The dashed lines represent the exposure fraction measured by EDDthreshold in historical period for corresponding crops and phenological stages. The dotted lines represent the exposure fraction measured by fixed 30 °C in historical period for corresponding crops and phenological stages. LOS, length of growing season.

Discussion

Accurate depiction of crop exposure to heat stress is fundamental for reliably quantifying extreme heat-induced yield loss and crop failure.

Previous studies have adopted spatially invariant but largely different thresholds for assessing extreme heat impact: some considered heat damage to maize and soybean occurs only above approximately 40 °C (refs. 12,13,26), whereas others used thresholds of 30 °C or even lower[9,27]. In addition, spatially fixed thresholds are often applied in many studies and standards. For example, in China, a national standard called 'Temperature index of high temperature harm' (GB/T 21985-2008) also suggest a fixed threshold to be applied over the entire nation, whose climate, over cropping zone vary largely for maize from the south (~20° N) to the north (~50° N). The large discrepancies in defining the threshold result in substantial variations in forecast/hindcast of heat-related risks. In this study, we supplement these experimental thresholds with our estimates from county-level yield statistics, reflecting the onset of yield decline under realized local environments and management. The spatially explicit threshold (EDDthreshold) for maize and soybean across the Northern Hemisphere demonstrates strong geographic heterogeneity and help narrowing discrepancies in prior assumptions about extreme heat exposure.

Several drivers of the spatial variations in the EDDthreshold could be identified. Our analyses using machine learning models revealed that climatic factors can explain as much as 30% of the spatial variations in EDDthreshold (Supplementary Figs. 13 and 14), highlighting climatic adaptation for extreme heat exposure[35]. Soil properties may also play a role, for instance, soils with higher water-holding capacities can buffer compound heat-drought stress, whereas soils with lower water-holding capacities may exacerbate extreme heat impacts[16].

The apparent adaptation, however, may not necessarily be automatic; it could result from breeding efforts36 or adaptive management such as irrigation. Existing management datasets are spatially coarse and aggregated, which limits detectability of fertilizer and irrigation effects at the global scale, we can only exploit regions where data are available. On the basis of the US county-level irrigation records, we found that EDDthreshold is significantly higher under irrigation (Supplementary Fig. 15), consistent with previous studies[22] showing irrigation mitigates exposure to extreme heat. The buffering capacity of irrigation, however, depends on water availability: in water-limited conditions, supplies may be insufficient to prevent deficits in soil moisture; thus irrigation cannot fully alleviate heat stress[37]. Consequently, a significant global signal is not detected even though local effects are clear—an outcome probably driven by the coarse resolution of global irrigation datasets and the inherent spatio-temporal heterogeneity of effective irrigation intensity, rather than any lack of importance of irrigation itself.

A plausible pathway for irrigation to reduce extreme heat exposure is by promoting crop transpiration, which effectively lowers canopy temperature[21,22,38,39], a thermal index found to shape crop heat stress even more than ambient air temperature[39]. However, most current crop models rely only on air temperature to drive heat accumulation, overlooking additional heat stress that dry soil conditions may bring into the micro-environment. Although the importance of canopy temperature for a crop's micro-environment has been widely recognized, using it to force crop models remain challenging: retrieving accurate canopy temperature from satellite remote sensing remains technically difficult[40], rendering global observational datasets of canopy temperature limited. Modelling canopy temperature is also not mature, particularly under concurrent drought and heat stress conditions, failing to reliably capture interactions between canopy temperature and moisture change[41].

In addition, benchmarking our results with state-of-the-art global crop models (Fig. 2 and Supplementary Table 2) further revealed several important limitations in current simulation of crop responses to extreme heat. For example, crop models are mostly calibrated with experiment or yield census. The prescribed EDDthreshold in models typically lower than observed EDDthreshold (Fig. 1e,f) causes models to over-estimate the extreme heat exposure, but they can still produce similar extreme heat-induced yield loss in the experiments/statistics by lowering modelled crop response to unit heat exposure[42] (vulnerability). Although this compensation between exposure and vulnerability might produce reasonable yield loss in the calibration dataset, when greater extreme heat events come, it would underestimate yield loss (see Schewe et al.[31]) due to its biased vulnerability (Extended Data Fig. 1). Moreover, applying spatially invariant extreme heat exposure thresholds fails to account for regional variation in heat resistance, which could also introduce systematic biases when simulating the impacts of extreme heat events over broader regions.

Looking into the future, the increasing exposure of crops to extreme heat is almost unavoidable. We consistently observed rising trends in extreme heat exposure across most major crop-producing regions in the Northern Hemisphere, regardless of scenarios, climate models and crop models used. Widely discussed adaptation strategies against extreme heat-induced yield loss such as adjusting the sowing dates and adopting new varieties to maintain the growing-season length[32,43,44] are, however, insufficient to fully offset escalating extreme heat exposure, even though considering the sensitive phenological stage to extreme heat could be advanced due to accelerated phenological development (Supplementary Fig. 20). Therefore, addressing the rise in extreme heat exposure requires not only more accurate projections from crop models but also the implementation of diverse and coordinated adaptive management strategies. At the field level, micro-climate regulation through precise irrigation scheduling and soil-cover management can further help alleviate excessive heat exposure[21].

The adaptation strategies we discussed above should be integrated into climate-smart agriculture framework[45], implementation of which could be supported by applying our spatially explicit EDDthreshold. Climate-smart agriculture promotes a holistic approach that not only ensures food security but also enhances the adaptive capacity and resource-use efficiency of agricultural systems, simultaneously achieving climate-mitigation goals through enhanced carbon sequestration and reduced greenhouse gas emissions[45]. As our results show that without effective global action reducing greenhouse gas emissions to limit global warming, the increasing risks of extreme climate events could not be easily adapted. Our choices in greenhouse gas emissions today largely shape the future food-security risks from extreme climate events.

Methods

Yield and ancillary data

The subnational yield data used in this study were obtained from the national statistic agencies during 2000–2019. For the USA, county-level data were obtained from the US Department of Agriculture (USDA) National Agricultural Statistics Service (www.nass.usda.gov). For the European Union and partner countries, NUTS2-leveldata were obtained from Eurostat (https://ec.europa.eu/eurostat). For Russia, state-level data were obtained from the Federal State Statistics Service (https:// rosstat.gov.ru/). For China, county-level data were obtained from the official agricultural statistical year books of each county or province. The yield data were subjected to an outlier filtering according to Schau-berger et al.46 because the statistical annotations were sometimes erroneous with unattainable value. We included only regions with yield records more than 10 years (Supplementary Fig. 23).

To identify regional-level crop development stages including silking or blooming and maturity dates and sowing dates were collected from a combination of site-based observations, statistical progress of crop phenology and satellite-derived data to make a crop calendar (Supplementary Fig. 24). The timing of corresponding stages are fixed as annual high-resolution observations were sparce. For the USA, weekly statistical phenological data were obtained from the USDA National Agricultural Statistics Service (www.nass.usda.gov). For each state-year phenological stage, the week where half of the crops had experienced the stage were chosen to represent for the stage. For China, daily phenological data were obtained from a satellite-derived product ChinaCropPhen[47] for maize at 1 km and from agricultural meteorological stations of the China Meteorological Administration (CMA, data. cma.cn) for soybean. A total of 65 stations with 1,430 site-year records were used in this study. For regions where subnational crop development data are not available, we use GGCMI global crop calendar48, which is a composite product merging various observational data. The whole growing season was divided into vegetative stage (from sowing or emerging to 10 days before flowering), anthesis (21 days around flowering) and grain filling stage (10 days after flowering to maturity) as described in Lobell et al.[3].

Global distributions of maize and soybean are derived from the Spatial Production Allocation Model (SPAM)49. We filtered regions where cropland had more than 5 years heat exposure (daily maximum temperature > 30 °C for more than 1 day within growing season) to assure the regions involved in the analysis did have experienced high temperature (Supplementary Fig. 25). A total of 3,929 counties for maize and 3,779 counties for soybean were selected, with the total number of records at 69,157 for maize and 67,012 for soybean.

Because the statistical yield records in subnational administrative units were not available to separate rain-fed and irrigated systems (only a few counties in the USA provide separated rain-fed and irrigated systems census), we use satellite-based irrigation cropland distribution to calculate the irrigated area fraction (in percentage of plant area). Irrigation distribution for croplands were obtained from Landsat-based Irrigation Dataset (LANID)50 at 30-m resolution, Eurostat (https://ec.europa.eu/eurostat) and a 500-m resolution irrigated croplands product in China[51]. These data were calibrated by cropland masks to confirm corresponding crops (that is, maize or soybean) were planted, using cropland distributions from the USDA Cropland Data Layer (CDL)[52] for USA or data from SPAM for other regions. Afterwards, the crop-specific irrigation areas were summed at subnational administrative units. We also obtained nitrogen, potassium, phosphorus application rate from a global crop-specific fertilization dataset[53]. It should also be noted that current global data on irrigation and fertilizer inputs are generally derived from information aggregated at national or large-regional scales and do not capture fine-scale variations, though their nominal spatial resolution is high (for example, ref. 54), which also partially explain why the statistical model could not detect robustly their influence. This should not be interpreted as that irrigation and other management practices are not important.

Climatic and edaphic data

Climate variables used in this study, including daily maximum or minimum 2-m air temperature and precipitation, were obtained from China Meteorological Forcing Dataset55 (CMFD, https://data.tpdc.ac.cn/ zh-hans/data/e60dfd96-5fd8-493f-beae-e8e5d24dece4) for China, from the E-OBS56 dataset (https://surfobs.climate.copernicus.eu/data-access/access_eobs.php) for Europe and from the PRISM[57] dataset (https://www.prism.oregonstate.edu/) for the USA, respectively. We also applied a bias-adjusted dataset using the WATCH Forcing Data methodology to surface meteorological variables from the ERA-5 reanalysis data (WFDE5, https://www.isimip.org/gettingstarted/input-data-bias-adjustment/details/114/)[58,59] to check the robustness to the input climate datasets (Supplementary Fig. 8). Downward surface solar radiation (Rs) and vapour pressure deficit were obtained from ERA-5 reanalysis datasets (https://cds.climate.copernicus.eu/). We obtained GLEAM460 root-zone soil moisture (https://www.gleam. eu/). Top soil (0–30 cm) characteristic data were retrieved from the Regridded Harmonized World Soil Database v.1.2 in the Oak Ridge National Laboratory Distributed Active Archive Center for Biogeo-chemical Dynamics (https://www.fao.org/soils-portal/soil-survey/ soil-maps-and-databases/harmonized-world-soil-database-v12/en/). Variables were resampled using average value in each administrative unit. The intra-county heterogeneities are not considered in this study (Supplementary Fig. 22).

Model simulation data

We used Phase 3 simulation results by Global Gridded Crop Model Intercomparison of the Agricultural Model Inter-comparison and Improvement Project (AgMIP), including 11 process-based crop models: CROVER, CYGMA, DSSAT-Pythia, EPIC-IIASA, ISAM, LDNDC, LPJmL, pDSSAT, PEPIC, PROMET and SIMPLACE-LINTUL5+.

Note that not all model simulated both crops, DSSAT-Pythia did not simulate soybean. These models are considered independent with different structures and assumptions; further details are described in Supplementary Table 2 and ref. 48. All crop models were driven by the same bias-adjusted weather dataset from five global climate models (GCM) in phase 6 of the coupled model intercomparison project (CMIP6)[48,61] at 0.5° × 0.5° spatial resolution, that is, GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0 and UKESM1-0-LL. These GCMs data were used to project future exposure in this study.

GGCM outputs including historical yield simulations and projected stages of growing period under SSP126 and SSP585 scenarios were used in this study. For some models who did not simulate anthesis, empirical flowering dates were set based on the averaged proportion of observational phenology period length in corresponding geographical units. Model outputs in the middle of the twenty-first century (2041–2060) and by the end of the twenty-first century (2081–2100) were included for future projections. All simulation data were resampled to subnational administrative units using regional averaged value, in accordance with the observational yield records.

Detection of EDDthreshold

Following the conventional concept which assume crop yield has a nonlinear thermal response[2,3], we calculated growing degree days (GDDs) and extreme degree days (EDDs):

$$\mathrm{GDD}_{\mathrm{base,upper}} = \frac{1}{24} \times \sum_{t=1}^{N} \mathrm{DD}_t, \mathrm{DD} = \left\{ \begin{array}{cc} T_{\mathrm{upper}} - T_{\mathrm{base}} & T_t \geq T_{\mathrm{upper}} \\ T_t - T_{\mathrm{base}} & T_{\mathrm{upper}} > T_t \geq T_{\mathrm{base}} \\ 0 & T_t < T_{\mathrm{base}} \end{array} \right\} \tag{1}$$

$$\mathrm{EDD} = \frac{1}{24} \times \sum_{t=1}^{N} \mathrm{DD}_t, \mathrm{DD} = \left\{ \begin{array}{cc} T_t - \mathrm{EDD}_{\mathrm{threshold}} & T_t \geq \mathrm{EDD}_{\mathrm{threshold}} \\ 0 & T_t < \mathrm{EDD}_{\mathrm{threshold}} \end{array} \right\} \tag{2}$$

where T_t is the hourly temperature calculated by sinusoidal interpolation between daily T_{min} and T_{max} following previous researches[3,17]. Degree days calculated by hourly temperature are regarded as a more accurate predictor of yield than daily temperature indicators[25]. N is the length of hours of county-specific growing period. EDD is a measure of exposure to temperatures above the extreme high-temperature threshold (EDDthreshold). Here we make EDDthreshold equals to the T_{upper} of GDD. We also tested a piecewise GDD which divide $GDD_{base,upper}$ into $GDD_{base,opt}$ and GDDopt,upper using a crop-specific optimal temperature parameter, T_{opt}. The calculations of these GDD terms follow the description in equation (1).

The EDDthreshold is defined as the air temperature at which EDD and GDD are best separated. Note that the threshold here is a statistical parameter in a dose–response function, not necessarily the same to the physiological constant under controlled experiment, and it reflects the onset of steep yield loss under local conditions. Canopy temperature is also of interest, but it is difficult to measure at large spatial and temporal scale because of the complexity of canopy structure and its interactions with microclimate[40,62]. Instead, the threshold of air temperature could be clearly defined and it provides a viable approach to investigate the variations. Further improvements to the extreme heat exposure estimation needs better accounting for the canopy temperature, which is part of the process that shaping the variation of the thresholds.

A multilinear regression was applied to each of the county to estimate the EDDthreshold. When estimating parameters for each county c, we only had a few observations at each county (up to 20 years); thus a time-series regression would not be able to reliably estimate the region-specific EDDthreshold. To overcome this limitation, we integrated spatial distance into our statistical model, which allow us to borrow data from nearby locations. For each county, we estimated the geodesic distance between the centroids of a county c0 and its nearby counties and got a rank of proximity, denoted as

$$c_0, c_1, c_2, \dots, c_i, \dots, c_n \qquad i = 0, 1, \dots, n \tag{3}$$

where c_1 is the nearest county to c_0, c_2 is the second nearest county to c_0, c_i is the ist nearest county to c_0 and c_n is the farthest county to c_0. The total number of counties is n. In this point of view, our spatially generalized statistical model, as an extension of the linear regression framework, could be exemplified by the following equation

$$Y_{c_i,t} = \sum_{k=1}^{m} \beta_{k,c_i} X_{c_i,t} + C_{c_i} + \varepsilon_{c_i,t}, i = 0, 1, \dots, r (0 \le r \le n) \tag{4}$$

where Y is the county-level yield, X contains m variables in county c_i and year t, C is a county-fixed constant which capture time-invariant effect and ε is an error term. We reported the results of X = (GDD, EDD, quad-ratic growing-season precipitation, quadratic yield trend). We also tested different specifications for the X in equation (4). (1) For GDD, a piecewise estimation of $GDD_{base,opt}$ and $GDD_{opt,upper}$ was applied (Supplementary Fig. 26a), instead of conventional $GDD_{base,upper}$. T_{min} and T_{opt} were defined according to Supplementary Table 3. (2) For the water-availability term, three proxies were tested, including precipitation for the 21-day period centred at anthesis (a period commonly recognized crops are more susceptible[3,33,41,63]), precipitation for the entire growing season and average root-zone soil moisture for the entire growing season. We also tested the alternative model using a linear precipitation term. (3) For the long-term trend of yield, linear or quadratic detrending was tested if the county had a significant trend; other-wise we subtracted the mean value. All these tests made little difference and gave similar distributions (Supplementary Figs. 3–7). Also, the distribution of EDDthreshold stimations was robust to the different selections of the GDD parameters (Supplementary Figs. 1 and 2), and different choices of variables of X (Supplementary Figs. 9–11).

For each specific county, we implemented a data-borrowing scheme that includes the r nearest neighbouring counties into the regression. We tested different values of the spatial pooling radii (the parameter r) and found the distribution of EDDthreshold remains similar when r < 10. The choice r = 7 corresponds to an effective neighbourhood scale of roughly 50 km on average, which is comparable to the 0.5° grid resolution of widely used global crop model simulations and gridded climate datasets. We also quantified uncertainty using a spatial block bootstrap and reported the standard deviation of the estimation. The uncertainty of the estimation of the threshold of extreme heat-induced yield loss in the majority counties is less than 2.5 °C (Supplementary Fig. 27).

We estimated equation (4) over all possible thresholds between T_{opt} (Supplementary Table 3) and the maximum air temperature within the entire growing season ($T_{\max gs}^{airmax}$) by changing EDDthreshold with a 0.2 °C step. For each possible EDDthreshold value, corresponding GDD, EDD and root-mean-square error (RMSE) of the regression model were calculated. Therefore, a temperature response curve of RMSE of the model was generated for each geographical unit. EDDthreshold was selected as the best fit where RMSE was minimized (Supplementary Fig. 26b). Using other model fitness indicators, such as Akaike Informa-tion Criterion or Bayesian Information Criterion, gave very similar estimates (Supplementary Fig. 21).

We compared our new estimates on EDDthreshold with heat thresh-olds reported by prior experimental studies (Supplementary Table 1). Our county-level estimates were generally consistent with thresholds observed from rain-fed field experiments but tended to be slightly lower than thresholds estimated under highly controlled chamber conditions. Compared with field experiments, controlled-environment experiment such as pot experiments can get different heat-threshold estimates because of factors including the artificially stable micro-climate (constant day–night temperature regimes), the location of temperature measurement (for example, ambient air, canopy surface or within-canopy conditions) and the phenological stage at which plants were exposed to heat stress (for example, pre-flowering or heading). These experimental thresholds typically reflect physiologically grounded limits under controlled conditions, whereas our statistically derived thresholds can represent realized responses that integrate local environmental and management influences. We also applied an up-to-date machine learning method, extreme gradient boosting (XGBoost), to quantify and interpret the contributions and potential nonlinearity among climatic factors, soil factors and agronomic factors on EDDthreshold. Supplementary Notes provide more details.

We also tried to extend the length of time periods in the USA, where long-term county-level yield census are available, to 1981–2020 (Supplementary Fig. 28). We found that the patterns of EDDthreshold remain stable in most counties, whereas higher values of thresholds have been shown in the latter period in around one-fifth counties for both maize and soybean. These changes could relate to the adoption to more extreme-resistant varieties[64,65] in the USA. Therefore, our results should be regarded as reflecting the distribution of EDDthreshold over the first two decades of the twenty-first century.

We note that the value of EDDthreshold in some mountainous or high-latitude regions (for example, Siberia and northeast China) should be treated with cautions because the extreme heat exposure of both crops remain rather limited (Supplementary Fig. 25). The scarce expo-sure implies EDDthreshold may exceed contemporary range of temperature variations so that the statistical method is not applicable. Thus, only areas with more than 5 years of over 30 °C temperature exposure were preserved. It should be noted that although we found relatively similar thresholds for the entire growing season as in the analysis with separate treatment of the anthesis and grain filling

(AGF) stages (Supplementary Fig. 12), experimental evidence indicates that these thresholds could be dependent on the development stage. For instance, a previous review reported the maximum cardinal temperature of maize at anthesis is 37.3 °C, whereas the threshold is 36.0 °C during grain filling66. Understanding stage-specific thresholds might help farmers optimize both planting dates and cultivar selection custom-made to their specific regions. Future research could focus on this. In addition, there is a significant level of uncertainty involved in capturing phenology through remotely sensed products, as the interannual crop phenology variations are inevitable.

Following the same statistical equation, we applied the EDDthreshold estimation on outputs of 11 crop models. We used simulated yield and corresponding climate variables from five GCMs, respectively. The results in Fig. 2a,b were the mean values across different climate and crop models (5 × 11 in total, DSSAT-Pythia did not simulate soybean).

Calculation of extreme heat exposure fraction

To evaluate the exposure to extreme heat of two crops, we estimated the exposure fraction difference as follows:

$$\mathrm{EF} = \frac{\sum_{t=1}^{N} \mu_t}{L} \times 100\%, \mu_t = \begin{Bmatrix} 1 & T_t \geq T_{\mathrm{base}} \\ 0 & T_t < T_{\mathrm{base}} \end{Bmatrix} \tag{5}$$

$$\text{exposure fraction difference} = \mathrm{EF}_{\mathrm{dynamic}} - \mathrm{EF}_{30\circ\mathrm{C}} \tag{6}$$

where EF is the exposure fraction to extreme heat, T_t follows the definition in equation (2) and L is the length of growing season. $EF_{dynamic}$ denotes that T_{base} equals to our data-driven EDDthreshold and EF30∘C denotes that T_{base} equals to 30 °C, the same as the threshold applied when the concept of EDD was first proposed[3]. Except to show the whole growing-season exposure fraction, we also illustrate the exposure fraction in the critical AGF stages. The extreme heat exposures for maize and soybean are more frequent during the AGF (Figs. 3 and 4). Moreover, we found that the surge in extreme heat exposure during anthesis cannot be compensated by the earlier flowering, which is induced by the acceleration of crop developments under warmer climates[34] (Supplementary Fig. 20).

Growing-season adaptation scenarios

The exposure to extreme heat could be altered through changing sowing date and the choice of cultivars. We estimated three potential adaptation managements by adjusting growing period: (1) apply time-constant growing-season length instead of heat-unit-dependent growing-season length used in crop models, assuming technological improvement through plant breeding by introducing long-maturity cultivars[32] to prolong growing season. (2) Apply adapted dynamic sowing dates instead of constant sowing dates used in crop models, assuming earlier planting under warming scenario to avoid terminal heat. (3) Apply (1) and (2) together. The growing season of crops are mostly temperature driven in the extratropical Northern Hemisphere[67]. Because the crop models use constant sowing dates for historical simulation and future scenarios, we applied dynamic sowing dates (DSOS) in each scenario by calculating the cumulative temperature in degree days (DD):

$$
\begin{cases}
\sum_{d=1}^{D_{\mathrm{SOS}}-1} \mathrm{DD}_d < \mathrm{GDD0}_{\min} \\
\sum_{d=1}^{D_{\mathrm{SOS}}} \mathrm{DD}_d \geq \mathrm{GDD0}_{\min} \\
\mathrm{GDD0}_{\min} = \sum_{d=1}^{\overline{\mathrm{SOS}}} \mathrm{DD}_d, \mathrm{DD} = \begin{cases} T_d - T_{\min} & T_d \geq T_{\min} \\ 0 & T_d < T_{\min} \end{cases}
\end{cases}
\quad (7)
$$

where D_{SOS} is the date of dynamic sowing dates under future scenario, d denotes the day of year and $GDD0_{min}$ is the minimum running accumulation of DD above T_{min} before sowing. T_{min} follows the definition in equation (1), and their values can be found in Supplementary Table 3. SOS is the averaged sowing day of growing season in historical period. The average dynamic sowing dates in the study area are projected to advance for a few days under SSP126 and for nearly a month under SSP585 by 2100 due to earlier spring (Supplementary Fig. 29).

Data availability

The air temperature threshold patterns for maize and soybean are avail-able via Zenodo at https://doi.org/10.5281/zenodo.17142122 (ref. 68). Data supporting the findings of this study are available within the article and/or its Supplementary Information files. Cropland distributions are from USDA Cropland Data Layer (https://www.nass.usda.gov/ Research_and_Science/Cropland/Release/index.php) and MapSPAM (https://mapspam.info/data/). Phenology data are from USDA National Agricultural Statistics Service (www.nass.usda.gov), China Meteorological Administration (data.cma.cn) and ChinaCropPhen (https://doi. org/10.6084/m9.figshare.8313530), and European Phenology data can be accessed upon request to G.Z. at gang.zhao@nwafu.edu.cn. Yield data are from USDA National Agricultural Statistics Service (www.nass. usda.gov), Eurostat (https://ec.europa.eu/eurostat) and Russian Federal State Statistics Service (https://rosstat.gov.ru/). Global production data in Fig. 1 is based on data from Food and Agriculture Organization of the United Nations (FAO, www.fao.org/faostat). Climate data are from China Meteorological Forcing Dataset (CMFD, https://data.tpdc.ac.cn/ zh-hans/data/e60dfd96-5fd8-493f-beae-e8e5d24dece4), E-OBS (https:// surfobs.climate.copernicus.eu/dataaccess/access_eobs.php), PRISM (https://www.prism.oregonstate.edu/), WFDE5 (https://www.isimip. org/gettingstarted/input-data-bias-adjustment/details/114/) and ERA-5 reanalysis datasets (https://cds.climate.copernicus.eu/). Regridded Harmonized World Soil Database v.1.2 is available at https://www.fao. org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/. The GGCMI crop calendar is accessible at https://doi.org/10.5281/zenodo.5062513. GGCMI phase 3 data can be accessed at https://data.isimip.org/search/tree/ISIMIP3b/OutputData/ agriculture/. GLEAM4 dataset can be accessed at https://www.gleam.eu/. Global crop-specific fertilization dataset is available at https://doi. org/10.6084/m9.figshare.25435432. The country-level boundaries are obtained from publicly accessible websites. World map and counties boundaries in the USA are from https://www.naturalearthdata.com/ downloads/10m-cultural-vectors/, in the European Union from https:// ec.europa.eu/eurostat/web/gisco/geodata/statistical-units/territorial-units-statistics, in Russia from https://simplemaps.com/gis/country/ru and in China from https://cloudcenter.tianditu.gov.cn/administrative-Division/. Source data are provided with this paper.

Code availability

The analyses were processed using MATLAB R2020a, ArcGIS 10.4 and Python 3.7. The code files can be accessed via figshare at https://fig-share.com/s/ea100e809648d85f2c77 (ref. 69).

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Author contributions

X.W. designed the study. Q.Z. collected statistical data and plotted all figures. Q.Z. and C.W. performed the analyses. G.Z. provided European phenology data. C.W., C.M., H.W., C.F., A.J., W.L., M.O., F. Zabel, J.J. and Y.J. provided crop model simulation data and experiment data. Q.Z., C.W. and X.W. wrote the first draft of the paper. All authors contributed to interpretation of the results and revision of the paper.

Competing interests

The authors declare no competing interests.

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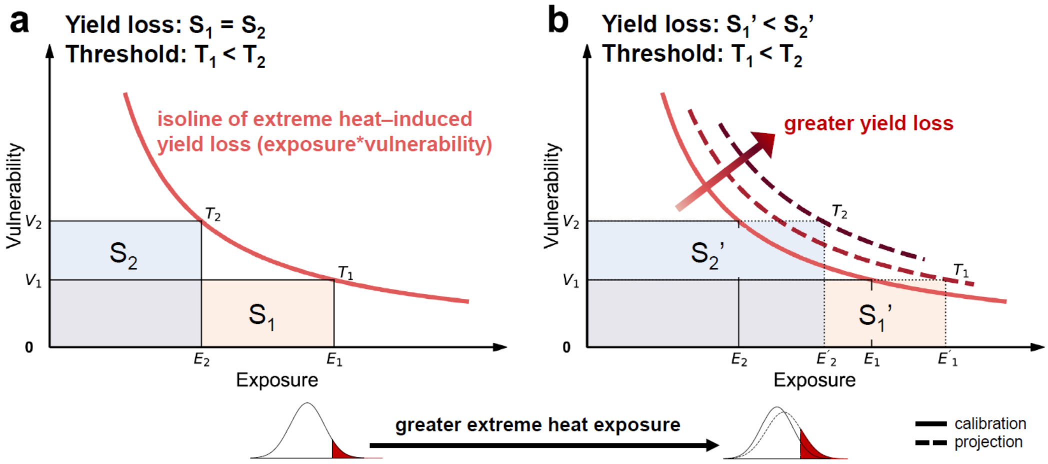
Supplementary figure



Extended Data Figure. 1 Conceptual diagram of how model underestimate in EDD threshold leads to its underestimate in extreme heat-induced yield loss. The extreme heat-induced yield loss (the color-shaded area) could be understood as the product of exposure (cumulated by EDD, x-axis) and vulnerability (marginal damage per unit extreme heat exposure, y-axis). a. Models can estimate similar extreme heat-induced yield loss (yield loss isoline, S1 = S2) with the trade-off in estimating the exposure and the vulnerability (that is lower EDD threshold (T1 < T2) leads to higher estimates on exposure (E1 > E2), which has to be balanced with lower estimates on vulnerability (V1 < V2)). b. When warming induces greater extreme heat exposure, models with underestimated EDD threshold (T1 < T2) and thus underestimated vulnerability (V1 < V2) will project underestimated yield loss (S1' < S2')