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Document Version

Author Accepted Manuscript (Postprint)

This version is available at

https://publications.pik-potsdam.de/pubman/item/item_31929

Originally published as

Fu, J., Wang, C., Qin, Y., Lesk, C., Müller, C., Zscheischler, J., Liu, X., Liang, H., Jian, Y., Wang, X., Zhou, F. (2025): Regionally variable responses of maize and soybean yield to rainfall events in China. - Agricultural and Forest Meteorology, 364, 110458.

<https://doi.org/10.1016/j.agrformet.2025.110458>

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Regionally Variable Responses of Maize and Soybean Yield to Rainfall Events in China

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Abstract

Understanding crop yield responses to rainfall is essential for food systems adaptation under climate change. While there are ample evidences of crop yield responses to seasonal rainfall variation, the geographic sensitivities and driving mechanisms of sub-seasonal rainfall events remain elusive. We used long-term nationwide observations to explore the sensitivity of maize and soybean yields in response to event-based rainfall across Chinese agroecological regions. While maize and soybean yield showed concave downward responses to event-based rainfall depth at the national scale, these responses were differed considerably among regions. These differences can be primarily explained by soil moisture preceding rainfall events, soil erosion and sunshine hour reduction during rainfall. Our projections reveal that focusing on seasonal rainfall or national-level sensitivity analysis suggests a 0.3-5.9% increase in maize yields due to future rainfall, yet considering spatial variations unveils a contrasting reality, with maize yields declining by $9.1 \pm 0.3\%$ under a medium-range emission scenario (SSP2-4.5) by the end of century (2085–2100). The future rainfall effect on soybean yield is the opposite, leading to a $20.6 \pm 3.9\%$ reduction nationally without spatial consideration, but an increase (by $7.0 \pm 1.0\%$) when spatial variations are factored in. These findings underscore the critical necessity of incorporating regional variation in yield responses to sub-seasonal rainfall events, which could otherwise lead to vastly different impact estimates, even reversing the expected crop yield response to future rainfall change.

Keywords: Sub-seasonal rainfall; Maize yield; Soybean yield; Sensitivity; Spatial heterogeneity.

1. Introduction

One third of global crop yield variability can be attributed to climate variations (Lobell and Field, 2007; Ray et al., 2015), but regionally, weather variations can explain much larger shares of yield variability (Müller et al., 2017). Compared to temperature, rainfall is not spatially coherent, showing increasing in northern China but decreasing in southeast China (Liu et al., 2015). Therefore, rainfall variabilities are strong at the regional scale and are projected to be amplified if greenhouse gas emissions increase (Huang et al., 2013; Marvel et al., 2019). It is thus necessary to quantify the impacts of rainfall on crop yields, including any spatial variations, to first assess the risk to food production, and then to develop targeted adaptive strategies to feed a burgeoning world population (Beillouin et al., 2020; Choi et al., 2024).

Geographic sensitivities of crop yields in response to rainfall remain largely unknown, and are widely omitted from crop models and climate risk projections (Li et al., 2019; Rosenzweig et al., 2002). On the one hand, the characteristics of rainfall, i.e. event size, frequency and duration, are highly heterogeneous over space and time. Spatially, yield statistics and climate variables aggregated at administration zones have likely muted the significance of highly localized rainfall (Lesk et al., 2016; Lobell and Burke, 2008). Temporally, the impacts of short-duration rainfall on crop yields are concealed in analyses using annual, seasonal or monthly climate data (Palmer et al., 2023; Troy et al., 2015; Zscheischler et al., 2020). Lesk et al. (2020) revealed that maize and soybean yields in the United States will benefit from future rainfall intensification. However, the generalizability of these yield responses to rainfall characteristics has yet to be confirmed in other regions.

Crop yield responses to rainfall events are regionally variable, as they reflect the interaction of many mechanisms and integrate effects of solar energy, water and temperature (Lesk et al., 2022; Lobell et al., 2009). Geographic sensitivities of crop yields in response to rainfall event are closely associated with the weather conditions that are induced by rainfall event, in addition to crop type, edaphic condition, and the

77 access to advanced agricultural technologies at a specific location ([Mueller et al., 2012](#)).
78 Further, crop yield responses to rainfall events may depend on regionally varying
79 connections between rainfall and other crop-relevant climate variables, such as
80 temperature, via surface energy partitioning ([Lesk et al., 2022](#); [Neumann et al., 2010](#)).
81 The lack of mechanistic understanding of the geographic differences in yield
82 sensitivities to rainfall events hinders evaluating historical rainfall effects on crop yields
83 and projecting the impacts of climate change in crop models ([Choi et al., 2024](#); [Webber
84 et al., 2020](#)). Spatially explicit information on the effect and relevant mechanism of
85 rainfall on crop production is instructive for agricultural production. For instance, it is
86 beneficial for farmers and agricultural advisory services to switch crop type, improve
87 water management and strengthen soil conservations, in capturing the benefits and
88 avoiding harms of rainfall events on crop yields.

89
90 Antecedent soil moisture has been posited to explain regional variation in crop yield
91 responses to seasonal total rainfall ([Li et al., 2023a](#)). It may also explain regional
92 variation in the impact of sub-seasonal rainfall events on yields, in addition to the other
93 factors (i.e., crop type and the access to advanced agricultural technologies). But this
94 remains unverified. For instance, excessive seasonal rainfall has contrasting effects on
95 crop yields across different regions. It significantly reduces crop yields in the United
96 States under the condition of high pre-season soil moisture ([Li et al., 2019](#)), alleviates
97 previous water deficit stress for crop yields in Africa ([Kabanda and Nenwiini, 2016](#);
98 [Muhire et al., 2015](#)), but had little effect on grain yields in regions with superior
99 irrigation and drainage conditions ([Togliatti et al., 2017](#)). Excessive seasonal rainfall
100 can suppress crop yields through waterlogging, submergence and lodging, as well as
101 the potential soil erosion, pests and diseases ([Kim et al., 2024](#)). Insufficient soil
102 moisture, on the contrary, slows soil organic matter decomposition ([Larsen et al., 2011](#))
103 and greatly affects the grain yields by reducing both the number and weight of seeds
104 ([Liu et al., 2008](#)). Low soil moisture increases soil water repellency, thereby enhancing
105 surface runoff and wind erosion ([Doerr et al., 2000](#); [Mäkinen et al., 2018](#)). The
106 threshold for soil moisture, at which point soil becomes water-repellent, can vary

widely from 2% to 40% by volume across different soil types (Goebel et al., 2011). Such differences in soil characteristics are expected to explain the geographic heterogeneities in crop yields response to rainfall in China (Gao et al., 2022; Liu et al., 2022).

Light availability can also be an important factor to explain the yields response to rainfall events. For instance, reduced light availability associated with rainfall events dominated the plant response to rainfall in Sweden, compared to rain characteristics and changes in water availability (Nijp et al., 2015). Reduced solar radiation was also responsible for the wheat yield failure of France in 2016, that contributing 31% to overall yield penalties followed by soil anoxia (26%) and physical damage on floret (19%) (Nóia Júnior et al., 2023). Decrease in solar radiation largely reduced the rice yield in the middle and lower reaches of the Yangtze River Basin and South Korea, while rarely impacting rice yield in Northeast China (Choi et al., 2013; Tao et al., 2013). As compared to the United States and the European Union, maize yield in China declined most strongly (−6%) in response to halving photosynthetically active radiation from 200 W m^{-2} over ten days, while maize yields in Brazil even increased (2.4%) under such radiation reduction (Proctor, 2021). As the dominant water supplier for rainfed crops and driver for solar radiation reduction, rainfall events largely determine crop yields potential ceiling and thus global food production (Lobell et al., 2009). Therefore, the effect of spatial variation in rainfall events on crop yields remain poorly represented and requires in-depth investigation.

Maize and soybean productions are of significant concern in China, because a possible decrease would exacerbate the structural shortage of domestic food and threaten the national food security (SCIO, 2019). To accurately evaluate the crop yields response to rainfall and its geographical varying sensitivity, we developed a statistical analysis of yields, event-based rainfall and weather measures from 179 stations for maize and 53 stations for soybean in China during 1999-2012. We compared the simulated yields sensitivities to rainfall events by process-based models to that from empirical models

based on field observations. We then disentangled the factors that determine the yields response to rainfall across different site clusters. Finally, future crop yields changes were projected under two climate change scenarios. Overall, we address three questions: (1) What are the geographic sensitivities of maize and soybean yields in response to rainfall events in China? (2) Which key factors govern the geographic variation in the yield sensitivity to rainfall? (3) Does accounting for regional variation in yield responses to rainfall events affect yield responses to future climate changes?

2. Data and methods

2.1 Data

We collected field observations of the meteorological indices for 1999-2012 from the network of China Meteorological Administration (CMA), including hourly rainfall, daily mean, maximum and minimum temperature (T_{mean} , T_{max} , T_{min}), sunshine duration (SSD), daily mean relative air humidity (RH) and wind speed (WS). This network provides observations at 2425 stations, covering maize and soybean fields in China ([Figure 1](#)). The annual station-level yields were obtained from the national agrometeorological observation network that is run by the CMA. The network has observed maize yields at 179 sites and soybean yields at 53 sites over the period 1999-2012. In total, there are 1488 maize yield observations and 460 soybean yield observations. Maize and soybean yields are defined as actual production (tons of dry matter) divided by the harvested area (hectares). Maize and soybean phenology that refers to the duration of the photosynthetically active period, were recorded for each site and year. The 0.1-degree gridded phenology were interpolated from field observed sowing and harvesting date of maize and soybean using the Inverse Distance Weight method. Gridded data were assigned the value of the nearest grid cell to site scales, to correspond with the end-of-season site-level yields data. We excluded grid cells with sowing area less than 1% from this study, to focus on the representative crop sowing regions. All datasets are freely available from the references with links listed in [Supplementary Table 1](#).

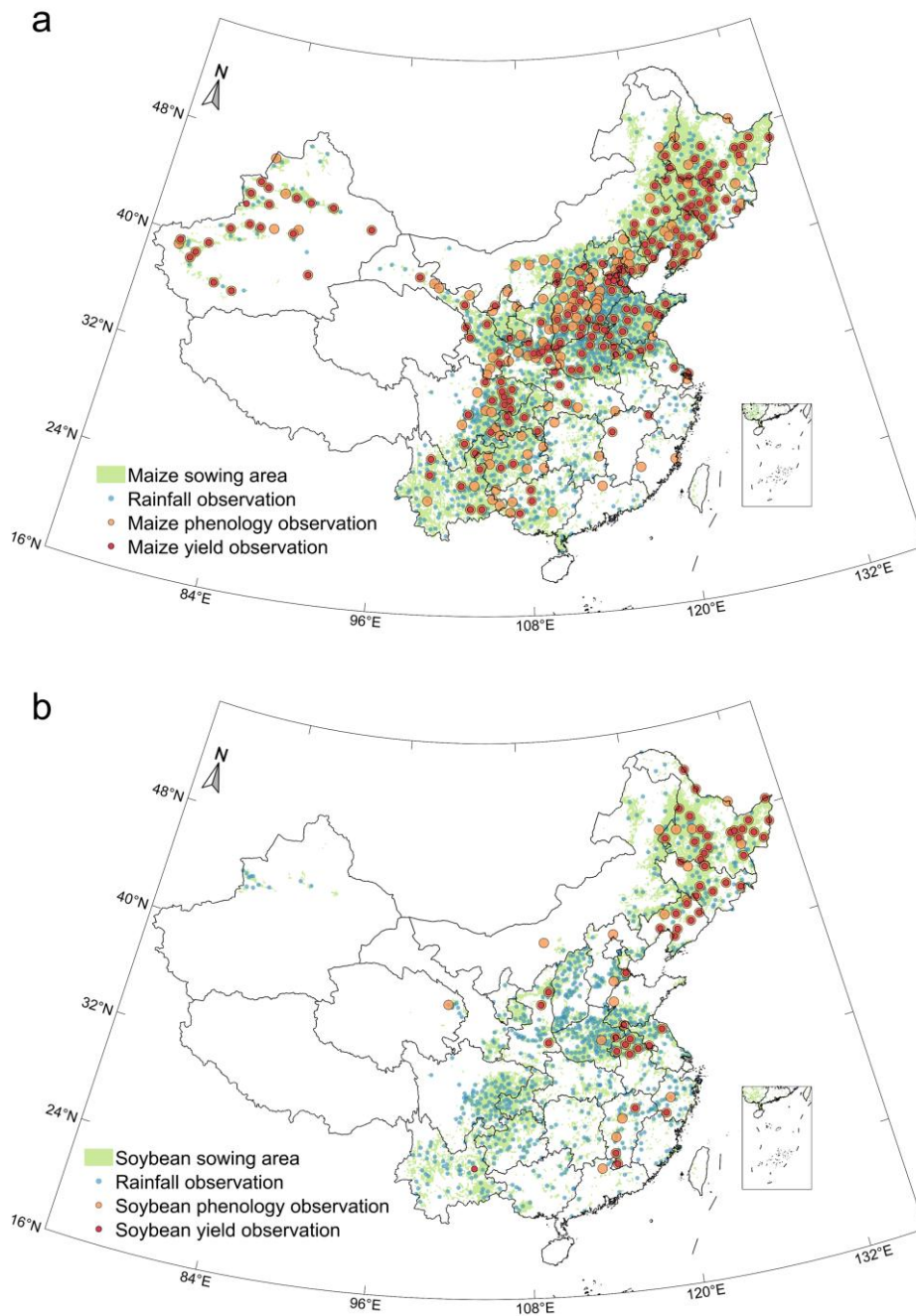


Fig. 1 Field observation network of **a.** maize and **b.** soybean yield, phenology, and rainfall within maize and soybean sowing areas during 1999-2012.

To test the spatiotemporal representativeness of the national agrometeorological observation stations in China, we conducted an additional analysis according to Beer et al. (2010). We compared the distributions of total rainfall and mean temperature during March-October between the datasets from stations with yield and phenology records in

1999-2012 (n=179 for maize, n = 53 for soybean) and all stations in the maize and soybean production areas in 1961-2015 (n= 1495 for maize, n = 873 for soybean). First, to test the representations of seasonal climate variation over space, we compared the distribution of daily mean temperature and total rainfall from study stations with those at all stations. Second, to test the representations of climate variation over time, we compared the kernel probability density curves of rainfall and mean temperature in 1999-2012 with that in 1961-2015. Kullback–Leibler divergence (KL) was used to evaluate the representativeness over times and space (van Erven and Harremoës, 2014). Climate datasets were acquired directly from the national agrometeorological observation stations, including 2195 stations within maize and 2268 stations within soybean production areas in China. Results showed that our dataset can adequately capture the spatiotemporal heterogeneity of climate conditions across maize and soybean production areas in China over space (Maize: $KL \leq 0.2$, Figures S1a-b; soybean: $KL \leq 0.4$, Figures S2a-b) and time (Maize: $KL \leq 0.2$, Figures S1c-d; soybean: $KL \leq 0.2$, Figures S2c-d).

2.2 Yield response to rainfall based on site observations

To investigate the spatial variations, we quantified the yield sensitivities of maize and soybean across China, four agroecological zones (northeast, northwest, southern China and North China Plain) and at a finer scale of site clusters (Figures S3-S5). More details regarding the climate and cropping system in the four agroecological zones are shown in Supplementary Table 2. The growing season of both maize and soybean lasted from March to October based on the national average during 1961-2021, covering growing season in the four agroecological zones. To further investigate variations of yield sensitivities at a finer scale, we clustered the sites using k-means clustering algorithm based on geographical locations and weather conditions. To ensure the adequate and comparable sample sizes, we set minimum thresholds of 50 data from at least 3 sites for each cluster, resulting in 33 site clusters for maize and 12 for soybean (Figure S5).

Rainfall events were identified following a standard with at least 6 h for the inter-event

time. The event-based rainfall data were aggregated to the seasonal scale by adopting moving window (ω) summarizing frequencies in each growing season and site. To make the sample sizes comparable between moving windows, the moving step and width of windows were set according to the distribution of event-based rainfall during the growing season. The site observed rainfall event during 1999-2012 were fitted to a Pearson III distribution by applying moving windows with a step size of 0.5 mm, resulting in 96 windows (Figures S3-S4). To ensure the adequate and comparable sample size within each window, the window width was set according to non-zero sample size that reached one-third of the site-year observations involved, that is 496 non-zero samples for maize and 153 for soybean at national scale.

To examine the effects on crop yields due to specific event-based rainfall depth, we applied a linear fixed-effects multiple regression model following Lesk et al. (2020):

$$Y_{z,t,u,\omega}^{fit} = \beta_0 E_{i,t,u} + \beta_{z,u,\omega} W_{i,t,u,\omega} + S_i, \quad \forall z, u, \quad (1)$$

where z refers to the national scale, regional scale and site clusters, i refers to sites within z . And t , u , ω refer to year, crop type, and moving window, respectively.

$Y_{z,t,u,\omega}^{fit}$ refers to the fitted yield. $E_{i,t,u}$ refers to environmental measures involving linear terms for growing degree days (GDD), diurnal temperature range (DTR), and T_{max} , SSD , as well as a quadratic term for seasonal total rainfall predictors ($PreT$).

We estimated the national/regional mean sensitivity of site-level yields to specific rainfall event size as the coefficient $\beta_{z,u,\omega}$ on frequency during growing season within window ω ($W_{i,t,u,\omega}$). To extrapolate the yield responses beyond environmental conditions observed in 1999-2012, we fitted the estimated yield responses ($\beta_{z,u,\omega}$) from each window to a four-knot restricted cubic spline at 0.05, 0.35, 0.65 and 0.95 quartiles of rainfall event depth at national and regional scale. To test the robustness of the yield sensitivities, we re-estimated the model using three and five knots and found consistent concave responses (Figures S3-S4). S_i refers to time-invariant effects to control for time-invariant heterogeneity at the regional scale.

To exclude the differences in cultivar replacements and yields in response to rainfall between sites, we detrended maize and soybean yields before regression for each site:

$$Y_{i,t,u}^{de} = Y_{i,t,u} - (\alpha_{i,u} \times Year_t + \beta_{i,u}) + \bar{Y}_{i,u}, \quad \forall i, u, \quad (2)$$

where $Y_{i,t,u}$ and $Y_{i,t,u}^{de}$ refer to crop yields before and after being detrended, respectively, at site i of crop type u in year t . $\alpha_{i,u}$ and $\beta_{i,u}$ refer to coefficients of the temporal linear trend of the observed crop yields ($Y_{i,u}$) against observational years. $\bar{Y}_{i,u}$ refers to the mean of $Y_{i,u}$ at site i of crop type u during the observational years.

2.3 Yield response to rainfall based on model simulations

To test capability of the current process-based models in capturing geographically distinct responses to rainfall, we choose historical yield simulations from the Global Gridded Crop Model Intercomparison (GGCMI) phase 3 dataset of the Agricultural Model Intercomparison and Improvement Project (AgMIP). We obtained the simulated maize and soybean yield datasets at 0.5 arc-degree spatial resolution from 11 global gridded crop models between 1999-2012 from Müller et al. (2019). All the 11 models were driven by AgMIP Modern-Era Restrospective Analysis for Research and Applications (AgMERRA) climate forcing including temperature, precipitation and solar radiation on a 6-hour or daily time step. The simulations were carried out with their own “fullharm” configuration based on the management and technology assumptions and inputs they typically use for simulations in the historical period (Elliott et al., 2015). We used the model output for the rainfed scenario, since rainfed maize and soybean currently make up about 74% and 76% of the Chinese sowing area (Zhang et al., 2022) and selected all the grid cells where field agrometeorological observations are located. The simulated yields were detrended before applying the linear fixed-effects multiple regression model (Equation 1), following the same procedure as field observed yields data, in order to assess the crop yields response to sub-seasonal variations in rainfall events.

2.4 Spatial drivers of yield sensitivities

To further investigate the spatial driving factors of maize and soybean yield sensitivities to rainfall event, we conducted correlation analyses of the yield sensitivities against all the potential climatic variables that can be varied by rainfall events, including: (1) daily mean relative soil moisture (*RSM*) and vapor pressure deficit (*VPD*) one day before rainfall; (2) changes in *RSM* before and after rainfall event; (3) changes in *SSD*, *DTR*, and T_{max} , T_{min} as well as T_{mean} during rainfall as compared with that in two days before and after; (4) soil erosion induced by rainfall event; (5) total waterlogging days during growing period; (6) the mean and maximum wind speed duration rainfall event of growing period; and (7) management practices of nitrogen (N) fertilizer application rate, irrigation amount and planting density for maize and soybean during 1999-2012. To characterize the plant-available water, root-zone soil moisture was estimated with relative soil moisture (0.10 m depth) that was obtained from a 1 km daily soil moisture dataset (Cheng et al., 2023). Waterlogging days were accumulated when daily mean relative soil moisture reached 90% (CMA, 2021). Daily mean *VPD* was estimated from near-surface *RH* and T_{mean} . Soil erosion was calculated if event-based rainfall is greater than or equal to 12 mm (Brown and Foster, 1987):

$$SL_{i,t,u,\gamma} = R_{i,t,u,\gamma} \cdot K_t \cdot LS_t \cdot C_{t,u} \cdot P_{t,u}, \quad (3)$$

where $SL_{i,t,u,\gamma}$ and $R_{i,t,u,\gamma}$ are the γ^{th} event-based rainfall induced soil loss (t ha^{-1}) and rainfall erosivity factor; K_t is the soil erodibility factor; LS_t is the topographical factor, $C_{t,u}$ is the land management factor and $P_{t,u}$ represents soil conservation practice factor. All the above measures are available from Li et al. (2023b), except that $R_{i,t,u,\gamma}$ is calculated following Chang et al. (2022):

$$R_{i,t,u,\gamma} = 1.811 \cdot I_{60,\gamma} \cdot \sum_{t=1}^d (0.29 [1 - 0.72 \exp(-0.082 i_{\gamma,t})] \cdot \Delta V_{\gamma,t}), \quad (4)$$

where $I_{60,\gamma}$ refers to the maximum 60-minute rainfall intensity in the γ^{th} rainfall event, d is the duration of the rainfall event (in hours), $\Delta V_{\gamma,t}$ and $i_{\gamma,t}$ are the rainfall volume (mm) and rainfall intensity (mm h^{-1}) at t^{th} hour of the γ^{th} rainfall event.

As a robustness check, we therefore performed a partial correlation analysis for above mentioned climatic variables. Results are consistent with that of the linear correlation

analysis that *RSM*, *SL* and changes in *SSD* are significantly correlated with maize yields change, while wind speed, changes in *RSM* and *SSD* are significantly correlated with soybean yields change (Figures S6). Then we applied the significant variables into a multiple regression model to capture the potential impacts of these driving factors at a scale of site clusters as follows:

$$\beta_{z,u,\omega}^{fit} = \beta_1 f(RSM)_{i,u,\omega} + \beta_2 f(SL)_{i,u,\omega} + \beta_3 f(PRE)_{i,u,\omega} + \beta_4 f(\Delta SSD)_{i,u,\omega} + \beta_5 f(\Delta RSM)_{i,u,\omega} + \beta_6 f(WS)_{i,u,\omega}, \forall z, u, \quad (5)$$

where $\beta_{z,u,\omega}^{fit}$ is the predicted $\beta_{z,u,\omega}$ of Eq (1) that is estimated at site cluster scale, *RSM* refers to mean relative soil moisture (%) preceding rainfall events within window ω for each site *i* of zone *z*. *SL* is the mean soil erosion induced by rainfall events ($t\ ha^{-1}$) that is fitted as quadratic expansion, *PreE* refers to event rainfall depth (mm event⁻¹) in the form of quadratic expansion, ΔSSD and ΔRSM are the mean changes in sunshine duration (h) and soil moisture (%) during rainfall events, and *WS* is mean wind speed ($m\ s^{-1}$) during rainfall. To ensure the sufficient sample size within each window and to remove the effects of uneven distribution of rainfall events, we set three windows of 0-20 mm, 20-60 mm, and >60 mm for each site cluster, according to the national concave yields' response to rainfall events.

2.5 Future projections of the contribution of rainfall to maize and soybean yields

We applied the empirical model to simulate yield responses to future rainfall in the Shared Socioeconomic Pathway (SSP) scenarios 2-4.5 and 5-8.5. To analyze the contribution of future rainfall to maize and soybean yield variations, we estimated the differences between yield simulations with (Y_w^{fit}) and without (Y_{wo}^{fit}) the rainfall processes divided by Y_w^{fit} in 2086-2100. The integrated effects of future temperature, rainfall and elevated $[CO_2]$ on maize and soybean yields were estimated as the relative differences between yield simulations in 2086-2100 and 2001-2012. To remove systematic deviations from the simulated historical climate, a trend-preserving bias correction was applied to preserve absolute changes in temperature and relative changes

in rainfall (Hempel et al., 2013). The CNRM-ESM2-1 model was developed by the National Center for Meteorological Research, CNRM/CERFACS modelling group (Séférian et al., 2019). The sixth version of the Model for Interdisciplinary Research on Climate (MIROC6) was produced by the Japanese research community (Tatebe et al., 2019). Both models provide historical and forecast hourly rainfall. Relative soil moisture was projected following the method of Zhu et al. (2020) according to future changes in rainfall used in this study. Yield sensitivities in response to rainfall events were estimated by Equation 5. Details on input data source for future projections are given in Supplementary Table 1.

Fertilization effect of atmospheric CO₂ ([CO₂] hereafter) on maize and soybean yields cannot be ignored, especially under the SSP5-8.5 scenario. The observed [CO₂] in China during 2001-2012, which was within [370, 404] ppm, was low compared to those of SSP2-4.5 ([594, 617] ppm) and SSP5-8.5 ([1025, 1064] ppm) (Séférian et al., 2019). To mimic the effects of elevated [CO₂] in the future, we adjusted the projected maize and soybean yield simulations based on potential changes induced by [CO₂], estimated from a meta-regression analysis of Free-Air CO₂ Enrichment (FACE) observations by Zhu et al. (2023). Maize and soybean sowing dates were estimated using the mean of historical observations during 2001-2012, while the length of the growing season is restricted by the historically observed *GDD*, i.e. $1460 \pm 157^{\circ}\text{C}$ for maize and for $1347 \pm 193^{\circ}\text{C}$ for soybean.

Future yields were simulated by the following equation similar with sensitivity estimation:

$$Y_{i,t,u}^{fit} = \beta_0 E_{i,t,u} + \sum_{\gamma} \beta_{z,u}^{fit} W_{i,t,u,\gamma} \quad (6)$$

We estimate the contribution of historical and future sub-seasonal rainfall to maize and soybean yields with regional sensitivities if *z* refers to site clusters, with a national uniform sensitivity if *z* refers to the national scale. Contribution of seasonal total rainfall to future yields were also estimated with $\beta_0 E_{i,t,u}$ divided by Y_w^{fit} in 2086-

2100. The contribution of future rainfall to maize and soybean yields in China was calculated as the weighting average of all the grids by sowing area of each crop.

3. Results

3.1 Yield response to rainfall change

We modelled the national mean sensitivities of maize and soybean yields to event-based rainfall during 1999-2012 as restricted cubic splines, shown with the 95% confidence bands of the bootstrap analysis (Figure 2, Supplementary Table 3). Both of the field-level maize and soybean yields showed a concave downward response to rainfall, with a sensitivity-maximizing event-based rainfall of 40 mm ($n=1948$, $P<0.001$). Maize yields decline by 24.4 kg ha^{-1} per exposure to $100 \text{ mm event}^{-1}$ rainfall in China ($P<0.001$). This reduction correspond to 0.3% of the national mean maize yield. Soybean yields decline by a larger amount of 112.0 kg ha^{-1} per exposure, or 4.4 % of the national mean ($P<0.001$). This is in contrast with less sensitive of soybean yields than maize yields in response to high rainfall depth in the United States, suggesting that differences between crops may also vary regionally (Lesk et al., 2020).

The sensitivities of maize yields to rainfall show considerable geographic variations. Rainfall within $60\text{-}100 \text{ mm event}^{-1}$ penalizes yields in northwest and southern China, has insignificant effect on yields in Northeast China ($P = 0.34$), but benefits yields in North China Plain (by 1.0 %, $P = 0.02$, Figure 2b). Soybean yields respond positively to rainfall in the range of $29.4\text{-}56.5 \text{ mm event}^{-1}$ in the North China Plain, but within a wider range of $8.8\text{-}60.6 \text{ mm event}^{-1}$ in Northeast China. However, when exposed to 80 mm event^{-1} rainfall, soybean yields in Northeast China decrease by 113 kg ha^{-1} per time, which is 1.8 times of the yield penalty in the North China Plain (Figure 2c).

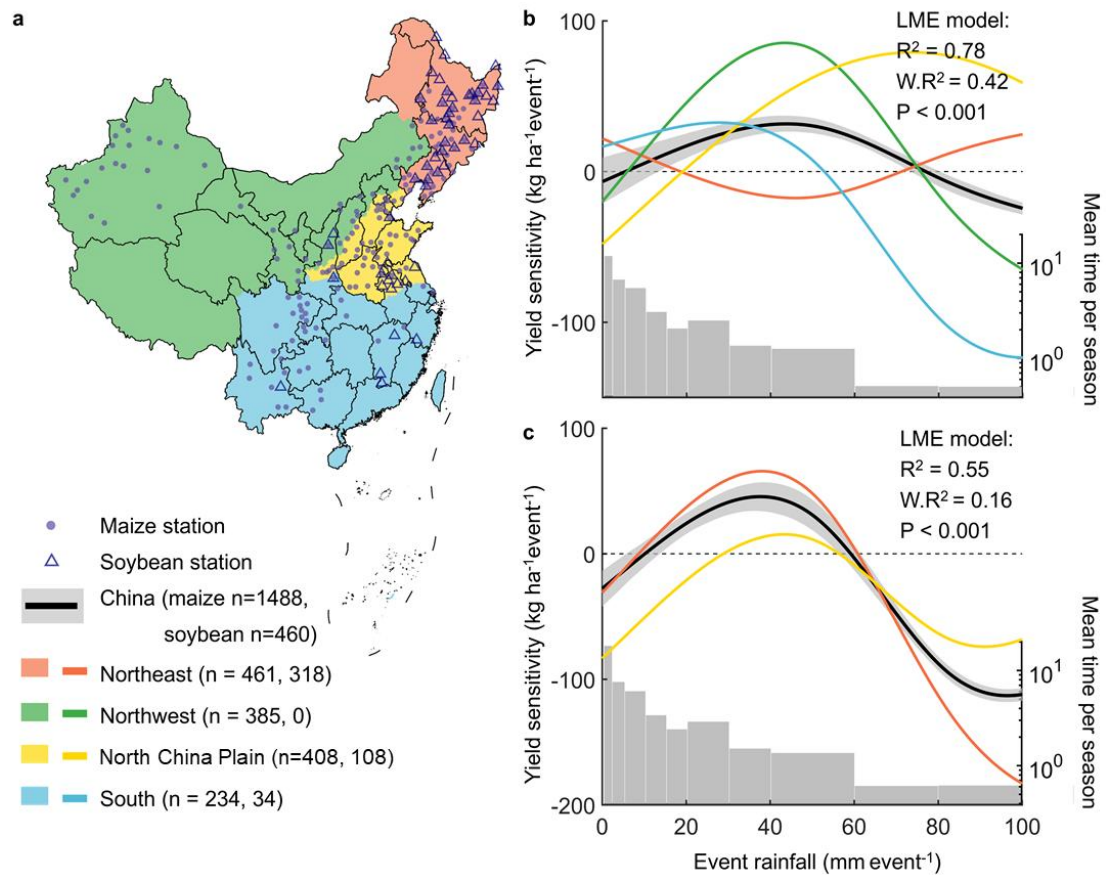


Figure 2 Distribution of **a.** agroecological zones and empirical estimates of sensitivity of **b.** maize (n=1488) and **c.** soybean (n=460) yields to event-based rainfall over 1999-2012. Results are shown nationally (black) and sub-nationally for the four major cropping regions of China. The sensitivities are inferred from a model controlling for exposure to beneficial and excessive heat and seasonal total rainfall. The shadow represents the 95% confidence intervals, estimated from 1,000-time bootstrap analysis. The histogram shows the distribution of event-based rainfall during the growing season.

Sensitivities of site level yields in response to hourly rainfall were insignificant (Figure S7), in comparison to the significant responses to site level event-based rainfall in China and administration level hourly rainfall in the United States (Lesk et al., 2020). This discrepancy probably relates to spatial resolution and climate backgrounds. First, aggregation of rainfall data to administration level may average the rainfall intensity, less representative for crop experienced rainfall intensities. Second, different climate backgrounds and rainfall characteristics in maize and soybean production areas were

found between China and the United States (Figure S8). Specifically, maize cropping regions in China faces longer rainfall duration and receive much less shortwave radiation as compared to the United States ($P < 0.001$). This could be one of the reasons for the largest sensitivity of yields to the reduction of total photosynthetically active radiation in China, comparing to the other main maize producing countries (Proctor, 2021).

To explore the ability of current models in capturing non-linear yield sensitivities to rainfall and their geographical variation, the sensitivities of simulated yields from the process-based model were compared with sensitivities estimated using statistical models. As most of the AgMIP crop models were run on a daily time step, they do not reflect the effect of event-based rainfall on crop yields (Figure S9-10), but still tend to be conservative about the nonlinear yield responses of daily rainfall and poorly capture the regional differences (Figure S11-12). The incapability of current models to simulate yield changes due to sub-seasonal rainfall may hinder our understanding on the mechanism of regional variations in yield response. These results highlight the need to incorporate a statistical model to analyze the sensitivity of crop yields to rainfall and potential mechanisms to explain their geographical differences.

3.2 Spatial drivers of yield sensitivities to rainfall change

To isolate drivers of the spatial variations of yield sensitivities to rainfall events, we regressed yield sensitivities ($\beta_{z,u,w}$) to indices of the rainfall potential accompanying processes for each site cluster (Figure 3). We found a quadratic response of maize yield sensitivities to soil moisture preceding rainfall events ($P = 0.024$) and changes in soil moisture during rainfall ($P < 0.001$; Figure 3a-b). Rainfall induced SSD deficit ($r = -0.38$, $P < 0.001$ for maize and $r = -0.29$, $P < 0.001$ for soybean) and soil erosion ($r = -0.18$, $P = 0.076$ for maize and $r = -0.48$, $P = 0.003$ for soybean) are linearly correlated with yield sensitivities (Figure 3c-d). Surprisingly, crop yields are more likely to be reduced by low wind speed (less than 1 m s^{-1}) than by high wind speed, suggesting that physical damage from wind during rainfall contributes little to crop yield reduction in China

(Figure 3e-f). A wind speed of less than 1 m s^{-1} is likely to be associated with at least 30 h of rainfall and 15 h of SSD deficit, leading to crop failure (Figure S13). This is consistent with previous studies that found SSD to be positively correlated with wind speed and negatively correlated with rainfall in China (Xiao et al., 2020; Yu et al., 2011). As for waterlogging days, changes in *VPD* and temperature-related factors, i.e. *DTR*, T_{max} , and T_{mean} , T_{min} induced by rainfall events, as well as management practices of N fertilizer application rate, irrigation amount and planting density, played a minor role in the spatial variation of yield sensitivity (Figure S14). These findings are robust to an alternative test of partial correlation analysis (Figure S6). Variables of e.g. rainfall induced soil erosion, sunshine duration reduction, and soil moisture were then involved in yield sensitivities predictions (Figure 4, Equation 5). Detailed model coefficients are listed in Supplementary Table 4.

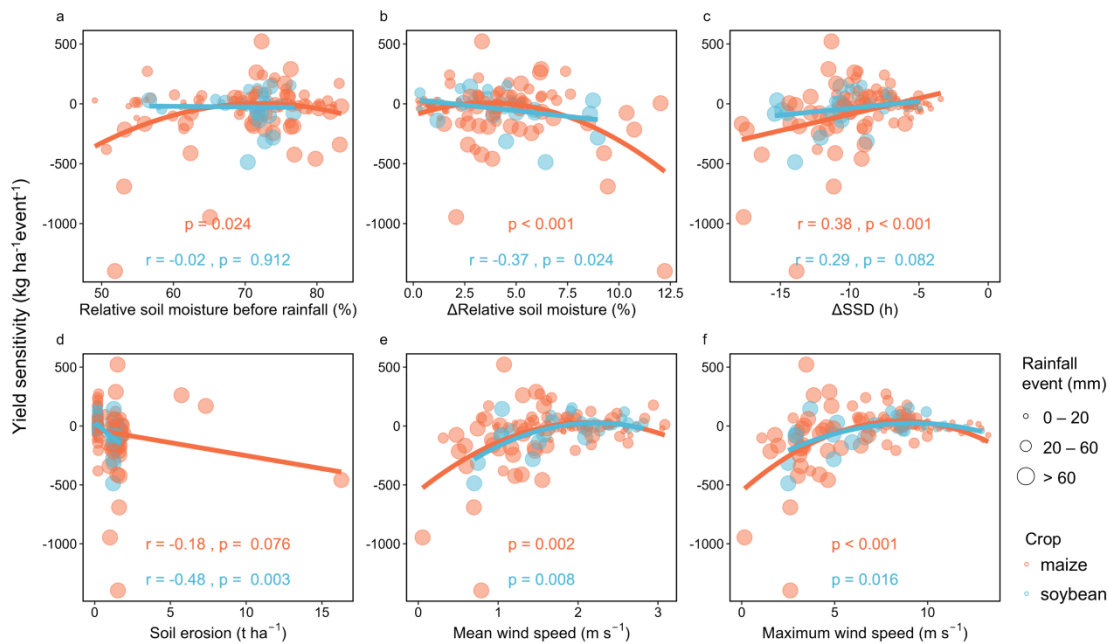


Figure 3 Relationship between yields sensitivity to environmental indices during rainfall or changed by rainfall in China. Orange indicates maize (n=99, from 33 site clusters) and cyan indicates soybean (n=36, from 12 site clusters). Three dot sizes indicate for three windows of event-based rainfall depths. The solid line is the best-fit line and the shaded area is the 95% confidence interval (estimated from 1,000-fold bootstrap analysis).

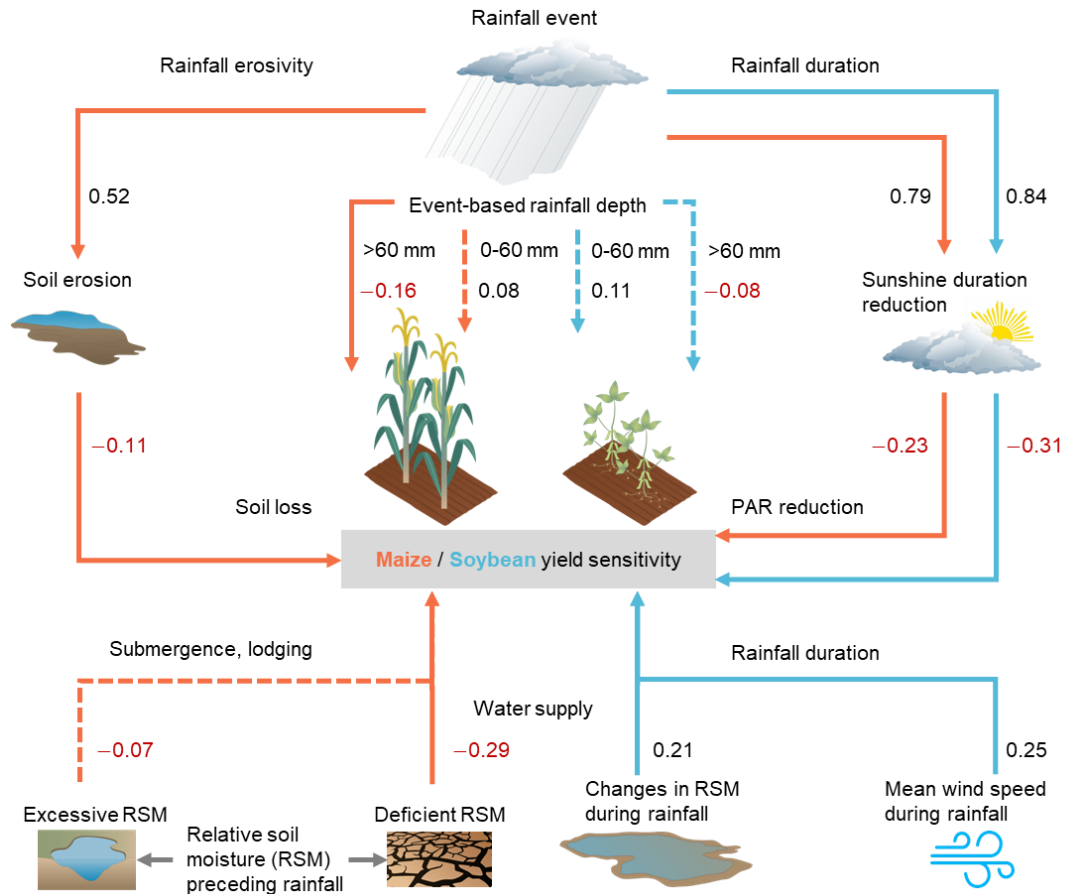


Figure 4 Schematic diagram of the main processes explaining the spatial differences in maize and soybean yield sensitivity to event-based rainfall. Orange indicates maize (n=99) and cyan indicates soybean (n=36). Solid arrows indicate significant effects ($P < 0.05$), while dotted lines indicate insignificant effects, with numbers representing standard coefficients of multiple linear regression models.

3.3 Future projections

To evaluate the significance of geographically varying framing conditions of the yield response to rainfall in future projections, we use event-based rainfall under the SSP2-4.5 and SSP5-8.5 scenarios by the end of this century (Figure 5). We keep all other variables constant to isolate the impacts of rainfall events. We find that maize yields increase by 0.3% when using a national sensitivity of response to intensifying rainfall event in both scenarios, while soybean yields decrease by 20.6-22.6%. These are in contrast with yield-benefiting effects that are projected if considering seasonally aggregated rainfall (Figure S15-16). Considering the observed geographical differences

of yields in response to sub-seasonal rainfall intensification, we project that maize yields would change by -9.1% and -10.6% under the SSP2-4.5 and the amplified SSP5-8.5 scenario, respectively. The national soybean yields benefit from historical rainfall by 7.4% when considering the geographically varying sensitivity, by 7.0% under SSP2-4.5 and by 6.7% under SSP5-8.5. Rainfall had an overall negative effect on maize yields in the four agroecological zones, e.g. ranging from -22.0% in the Northwest China to -6.0% in the North China Plain under SSP5-8.5, and on soybean yields in the North China Plain (-6.5%), while it benefited soybean yields in Northeast China (Figure 5, Figure S17). Maize yields in China increase by 1.5% per 10% increase in rainfall frequency, decrease by 1.7% per 10% increase in rainfall duration, and show little response to rainfall intensity, except in the North China Plain (-2.3% , Figure S18). Soybean yields in the North China Plain also decrease by 2.3% per 10% increase in rainfall intensity and by 0.7% per 10% increase in rainfall duration. Results are robust against the projected climate indices obtained from the CNRM-ESM2-1 and the MIROC6 model (Figure S19-20). The projected yields in response to climate change are comparable to the results from the Global Gridded Crop Model Intercomparisons (GGCMI) Phase 3 (Figures S21). However, the contribution of rainfall to the projected maize yield deficit and soybean yield increase is generally underestimated by 77% and 63% , respectively, in China under the SSP5-8.5 scenario (Figures S22).

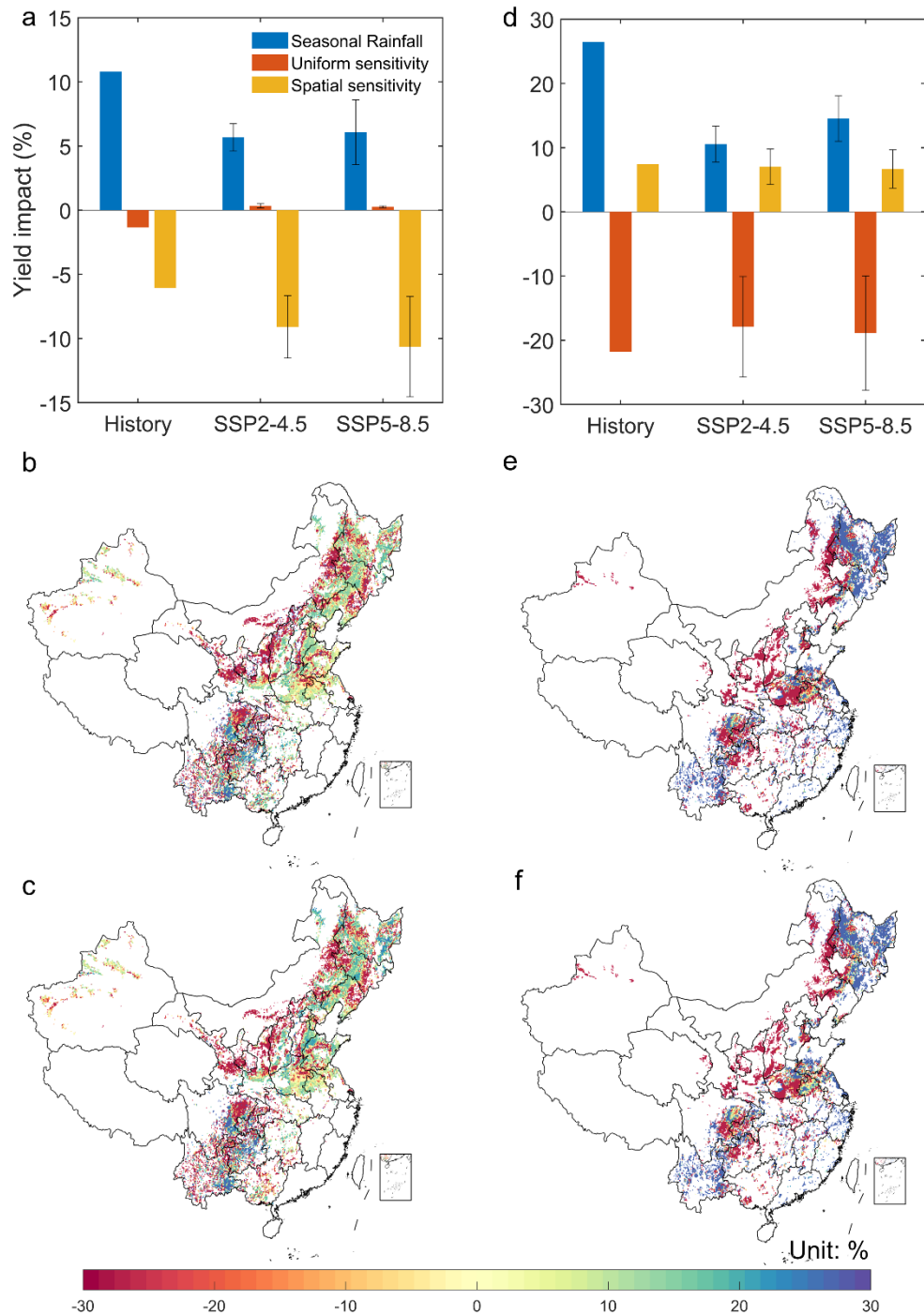


Fig. 5 Rainfall impacts on maize and soybean yields by the end of the century (2085-2100). Rainfall impacts on maize (a) and soybean (d) yields. b-c. Patterns of maize yields impact of geographic sub-seasonal rainfall events under SSP2-4.5 (b) and SSP5-8.5 (c). e-f. Patterns of soybean yields impact under SSP2-4.5 (e) and SSP5-8.5 (f). Columns show mean $\pm$ standard deviation of yield impact from climate simulations of the MIROC6 model and the CNRM-ESM2-1 model.

4. Discussion

Our study provided evidence on the sensitivities of maize and soybean yields to event-based rainfall in China, and investigated the driving factors that lead to geographic differences. Spatial variations in soil moisture, solar radiation reduction, soil erosion and wind speed partially explained the geographic differences in crop yield sensitivities. This in turn emphasized the effect of rainfall on crop yields, not only through physical damage, but also through water supply and radiation that largely determined yield potential ceiling for a given site and genotype. Without accounting for the contextual environmental and management conditions, future yield projections were subject to large uncertainties. As demonstrated by the exemplary application of region-specific and national average models, the future impacts of rainfall on crop yields in China was sensitive to the consideration of regional heterogeneity. Ignoring this diversity of production conditions would lead to errors (in our example an overestimation of maize yields by 7.2% and an underestimation of soybean yields by 25% under the SSP2-4.5 scenario by the end of the century).

4.1 Soil moisture and irrigation

Soil moisture is important for accurately predicting crop yield, has a non-linear correlation with crop yield, and determines the magnitude and even the direction of the high temperature effect on crop yield (Rigden et al., 2020; Ting et al., 2023). Excessive soil moisture restricts O₂ diffusion and mitochondrial respiration of plants and activates anaerobic microbes, while drought severely reduces photosynthetic capacity, adversely affecting plant growth and productivity. Maintaining soil moisture through irrigation has been widely proposed as an adaptation strategy to mitigate climate change (Qin, 2021). In this study, irrigation has an insignificant effect on maize and soybean yields in response to rainfall variability for two reasons: i) the current prefecture-level irrigation amount for specific crops hardly reflects the station-level irrigation amount; ii) lack of information on the time and frequency of irrigation during the growing season hinders further analysis of regionally variable irrigation efficiency and its effect on crop

yields. Intensive surveys or direct measurements using high-resolution remote sensing are therefore needed to unravel irrigation schemes at station level across China.

4.2 Sunshine duration and row spacing

Sunshine duration decreased linearly at a rate of -1.4h yr^{-1} between 2002 and 2021, leading to widespread yield reductions in China (Zhang, 2023). To improve the use of light energy, row spacing is being reduced to achieve a greater biomass production during the early growth and thus in an increased crop transpiration (Drouet and Kiniry, 2008). Late in growth, potential mutual shading could reduce the light transmittance, accelerate leaf senescence and disrupt photosynthetic characteristics (Raza et al., 2021). The effect of narrowing row spacing on yield is highly dependent on irrigation and fertilizer application rates, which can increase maize yields by up to 23% in rain-fed or unfertilized crops, but have a negligible effect on maize without water or N limitation (Andrade et al., 2002). In China, 90% of the total sown area is under adequate or excessive N fertilizer application (Ju and Gu, 2014). Irrigation efficiency has also improved since the 1950s with the creation of irrigation districts and the reform of agricultural water pricing. This is also the reason why field management in terms of N fertilizer application rate and row spacing had insignificant effect on maize and soybean yields and their response to rainfall in China.

4.3 Soil erosion and fertilizer application

Soil erosion has been one of the main limiting factors for maize production in China since the 1980s, correlating with a significant decline in the use of organic fertilizer and green manure (Wang and Li, 2010). First, eroded soils are characterized by shallow topsoil depths and reduced water and nutrient retention capacity, resulting in poor seedbed conditions that reduce crop seed emergence rates (Lin et al., 2019). Second, soil erosion preferentially removes fine soil particles and light organic matter fractions from the topsoil, altering soil structure, and inhibiting the rapid growth of fungi, which have a strong impact on available nutrient content, soil organic matter mineralization and sequestration (Trivedi et al., 2013; Xiao et al., 2018). Long-term application of

organic fertilizer, such as farmyard manure, could significantly improve maize yield on degraded soils. Third, the shallow topsoil depth, which limits the rooting depth of the crop, especially for crops with deeper rooting depths, e.g. maize and soybean, compared to wheat. Shallow rooting has a major impact on crop yield due to competitive root proliferation in the presence of neighbors (Vain et al., 2023).

4.4 Uncertainties and future work

Our estimates are subject to several sources of uncertainties. First, rainfall event size at regional scale remained largely uncertain in future projections, as the duration-intensity relationship may vary under climate change. The same applies to soil moisture projection, which was still in its infancy, despite being a key hydrologic state variable that directly affects the global environment and human society (Babaeian et al., 2019).

The timing of rainfall remained highly uncertain, as its effect on soil moisture is highly dependent on growing periods. Another source of uncertainty was introduced by bias-correction, that each climatic variable was bias-corrected separately, probably destroying their correlation, and further influencing the projection of soil moisture, e.g., heavy rainfall leads to a large change in radiation (Lange, 2019). Therefore, we projected future soil moisture based on natural forcing of temperature, event-based rainfall depth and frequency following Zhu et al. (2020). Note that the projection does not consider anthropogenic activities and land cover changes, such as afforestation practices, urbanization, and agricultural water management that affects the water cycle.

Second, the historically derived yield sensitivity may not hold by the end of the century. To meet a suite of agricultural sustainable development targets, cultivar selection, phenology optimization (Minoli et al., 2022), and crop switching (Xie et al., 2023) would further facilitate the adaptation to local climate change. Future climate change may increase the irrigation water demand of crop fields by changing the seasonal distribution of rainfall, soil moisture and vapor water deficit, while limiting the supply of irrigation water resources through increased inter-industry and inter-regional water competition (Wada et al., 2016). Irrational irrigation practices and water wastage,

caused for example by ageing or damaged irrigation equipment, would make matters worse. It is therefore likely that the capacity and efficiency of water management will widen the current geographical variation in crop yield sensitivities to rainfall. In addition, soil quality could be improved to better support crop production, by increasing soil organic matter content and optimizing N fertilizer application, which could increase the resilience of the farming system to rainfall variability in the future. Third, to account for the fertilization effect of rising [CO₂], the projected yield simulations of our statistical model were adjusted according to a meta-regression analysis. We also find that the [CO₂] fertilization effect is complicated by soil fertility and drought, in addition to crop type and temperature, which requires further extensive field experiments.

Future work may investigate the importance of rainfall timing, particularly in relation to different crop growth stages and regionally varying growing seasons. Variables such as crop cultivars, pests, and diseases due to limited spatial resolution are likely to influence or moderate yield responses, and may explain the regional variations observed in this study. Process-based models need to be improved to better capture the effects of crop yields in response to rainfall, their geographical differentiations and adaptation strategies. It is essential to empower farmers with spatially disaggregated information regarding their respective risk exposure, so that they can develop region- and crop-specific risk management and adaptation strategies, and thereby promoting improved resilience against climate change. In addition to improving domestic maize and soybean yields, future studies are needed to optimize in the spatial distribution of crops and avoid food loss and waste throughout the food supply chain. The reallocation of soybean area from Northeast China to North China needs to be carefully considered given the high sensitivity of soybean to future rainfall variability in the North China Plain. The improvement in domestic production and use efficiency of maize and soybean in China can also mitigate the pressures of international trade and the imported environmental impacts.

Acknowledgement

This study was supported by the National Natural Science Foundation of China (42361144876, 42225102, 42007079).

Appendix A. Supplementary data

Supplementary information related to this article can be found online, including Supplementary Tables 1 to 4, and Figures S1 to S22.

Author contributions

Feng Zhou: Conceptualization, Writing—review and editing, Funding acquisition and Project administration. **Jin Fu:** Investigation, Results Interpretation and Writing original draft. **Chengjie Wang:** Methodology, Formal analysis and Visualization. **Yue Qin:** Writing – review and editing. **Corey Lesk:** Writing – review and editing. **Christoph Müller:** Writing – review and editing. **Jakob Zscheischler:** Writing – review and editing. **Xuhui Wang:** Writing – review and editing. All co-authors reviewed and commented on the manuscript.

Conflicts of interest

The authors declare no conflicts of interest.

References

- Andrade, F.H., Calviño, P., Cirilo, A. and Barbieri, P., 2002. Yield responses to narrow rows depend on increased radiation interception. *Agron J*, 94(5): 975-980.
- Babaeian, E. et al., 2019. Ground, Proximal, and Satellite Remote Sensing of Soil Moisture. *Rev Geophys*, 57(2): 530-616.
- Beer, C. et al., 2010. Terrestrial Gross Carbon Dioxide Uptake: Global Distribution and Covariation with Climate. *Science*, 329(5993): 834-838.
- Beillouin, D., Schauburger, B., Bastos, A., Ciais, P. and Makowski, D., 2020. Impact of extreme weather conditions on European crop production in 2018. *Philos T R Soc B*, 375(1810): 20190510.
- Brown, L.C. and Foster, G.R., 1987. Storm Erosivity Using Idealized Intensity Distributions. *T Asae*, 30(2): 379-386.

- Chang, Y.M., Lei, H.M., Zhou, F. and Yang, D.W., 2022. Spatial and temporal variations of rainfall erosivity in the middle Yellow River Basin based on hourly rainfall data. *Catena*, 216: 106406.
- Cheng, F. et al., 2023. ChinaCropSM1 km: a fine 1 km daily soil moisture dataset for dryland wheat and maize across China during 1993–2018. *Earth Syst Sci Data*, 15(1): 395–409.
- Choi, E., Rigden, A.J., Tangdamrongsub, N., Jasinski, M.F. and Mueller, N.D., 2024. US crop yield losses from hydroclimatic hazards. *Environ Res Lett*, 19(1): 014005.
- Choi, W.J., Lee, M.S., Choi, J.E., Yoon, S. and Kim, H.Y., 2013. How do weather extremes affect rice productivity in a changing climate? An answer to episodic lack of sunshine. *Global Change Biol*, 19(4): 1300–1310.
- CMA, 2021. Grade of waterlogging for summer maize (QX/T583–2020). China Zhijian Publishing House, Beijing, China.
- Doerr, S.H., Shakesby, R.A. and Walsh, R.P.D., 2000. Soil water repellency: its causes, characteristics and hydro-geomorphological significance. *Earth–Sci Rev*, 51(1–4): 33–65.
- Drouet, J.L. and Kiniry, J.R., 2008. Does spatial arrangement of 3D plants affect light transmission and extinction coefficient within maize crops? *Field Crop Res*, 107(1): 62–69.
- Elliott, J. et al., 2015. The Global Gridded Crop Model Intercomparison: data and modeling protocols for Phase 1 (v1.0). *Geosci Model Dev*, 8(2): 261–277.
- Gao, Y.K. et al., 2022. Spatial and temporal variations of maize and wheat yield gaps and their relationships with climate in China. *Agr Water Manage*, 270: 107714.
- Goebel, M.O., Bachmann, J., Reichstein, M., Janssens, I.A. and Guggenberger, G., 2011. Soil water repellency and its implications for organic matter decomposition – is there a link to extreme climatic events? *Global Change Biol*, 17(8): 2640–2656.
- Hempel, S., Frieler, K., Warszawski, L., Schewe, J. and Piontek, F., 2013. A trend-preserving bias correction – the ISI-MIP approach. *Earth Syst Dynam*, 4(2): 219–236.
- Huang, P., Xie, S.P., Hu, K.M., Huang, G. and Huang, R.H., 2013. Patterns of the seasonal response of tropical rainfall to global warming. *Nat Geosci*, 6(5): 357–361.
- Ju, X.T. and Gu, B.J., 2014. Status-quo, problem and trend of nitrogen fertilization in China. *Journal of Plant Nutrition and Fertilizers*, 20(4): 783–795.(In Chinese with English abstract).
- Kabanda, T. and Nenwiini, S., 2016. Impacts of climate variation on the length of the rainfall season: an analysis of spatial patterns in North-East South Africa. *Theor Appl Climatol*, 125(1–2): 93–100.
- Kim, Y.U. et al., 2024. Mechanisms and modelling approaches for excessive rainfall stress on cereals: Waterlogging, submergence, lodging, pests and diseases. *Agr Forest Meteorol*, 344: 109819.
- Lange, S., 2019. Trend-preserving bias adjustment and statistical downscaling with ISIMIP3BASD (v1.0). *Geosci Model Dev*, 12(7): 3055–3070.
- Larsen, K.S. et al., 2011. Reduced N cycling in response to elevated CO₂, warming, and drought in a Danish heathland: Synthesizing results of the CLIMAITE project after two years of treatments. *Global Change Biol*, 17(5): 1884–1899.
- Lesk, C. et al., 2022. Compound heat and moisture extreme impacts on global crop yields under climate change. *Nat Rev Earth Env*, 3(12): 872–889.
- Lesk, C., Coffel, E. and Horton, R., 2020. Net benefits to US soy and maize yields from intensifying hourly rainfall. *Nat Clim Change*, 10(9): 819–822.

674 Lesk, C., Rowhani, P. and Ramankutty, N., 2016. Influence of extreme weather disasters on global
675 crop production. *Nature*, 529(7584): 84-87.

676 Li, H. et al., 2023a. Land-atmosphere feedbacks contribute to crop failure in global rainfed
677 breadbaskets. *Npj Clim Atmos Sci*, 6(1): 51.

678 Li, J.L., He, H.B., Zeng, Q.H., Chen, L.D. and Sun, R.H., 2023b. A Chinese soil conservation dataset
679 preventing soil water erosion from 1992 to 2019. *Sci Data*, 10(1): 319.

680 Li, Y., Guan, K.Y., Schnitkey, G.D., DeLucia, E. and Peng, B., 2019. Excessive rainfall leads to maize
681 yield loss of a comparable magnitude to extreme drought in the United States. *Global*
682 *Change Biol*, 25(7): 2325-2337.

683 Lin, H.H., Xie, Y., Liu, G., Zhai, J.R. and Li, S., 2019. Soybean and maize simulation under different
684 degrees of soil erosion. *Field Crop Res*, 230: 1-10.

685 Liu, J.B. et al., 2015. Holocene East Asian summer monsoon records in northern China and their
686 inconsistency with Chinese stalagmite $\delta^{18}\text{O}$ records. *Earth-Sci Rev*, 148: 194-208.

687 Liu, S.L. et al., 2022. Probability of maize yield failure increases with drought occurrence but
688 partially depends on local conditions in China. *Eur J Agron*, 139: 126552.

689 Liu, X., Jin, H., Wang, G.H. and Herbert, S.J., 2008. Soybean yield physiology and development of
690 high-yielding practices in Northeast China. *Field Crop Res*, 105(3): 157-171.

691 Lobell, D.B. and Burke, M.B., 2008. Why are agricultural impacts of climate change so uncertain?
692 The importance of temperature relative to precipitation. *Environ Res Lett*, 3(3): 034007.

693 Lobell, D.B., Cassman, K.G. and Field, C.B., 2009. Crop Yield Gaps: Their Importance, Magnitudes,
694 and Causes. *Annu Rev Env Resour*, 34: 179-204.

695 Lobell, D.B. and Field, C.B., 2007. Global scale climate - crop yield relationships and the impacts of
696 recent warming. *Environ Res Lett*, 2(1): 014002.

697 Mäkinen, H. et al., 2018. Sensitivity of European wheat to extreme weather. *Field Crop Res*, 222:
698 209-217.

699 Marvel, K. et al., 2019. Twentieth-century hydroclimate changes consistent with human influence.
700 *Nature*, 569(7754): 59-65.

701 Minoli, S., Jägermeyr, J., Asseng, S., Urfels, A. and Müller, C., 2022. Global crop yields can be lifted
702 by timely adaptation of growing periods to climate change. *Nat Commun*, 13(1): 7079.

703 Mueller, N.D. et al., 2012. Closing yield gaps through nutrient and water management. *Nature*,
704 490(7419): 254-257.

705 Muhire, I., Ahmed, F., Abutaleb, K. and Kabera, G., 2015. Impacts of projected changes and
706 variability in climatic data on major food crops yields in Rwanda. *Int J Plant Prod*, 9(3):
707 347-371.

708 Müller, C. et al., 2017. Global gridded crop model evaluation: benchmarking, skills, deficiencies
709 and implications. *Geosci Model Dev*, 10(4): 1403-1422.

710 Müller, C. et al., 2019. The Global Gridded Crop Model Intercomparison phase 1 simulation dataset.
711 *Sci Data*, 6: 50.

712 Neumann, K., Verburg, P.H., Stehfest, E. and Müller, C., 2010. The yield gap of global grain
713 production: A spatial analysis. *Agr Syst*, 103(5): 316-326.

714 Nijp, J.J. et al., 2015. Rain events decrease boreal peatland net CO₂ uptake through reduced light
715 availability. *Global Change Biol*, 21(6): 2309-2320.

716 Nória Júnior, R.d.S. et al., 2023. The extreme 2016 wheat yield failure in France. *Global Change Biol*,
717 29(11): 3130-3146.

718 Palmer, P.I. et al., 2023. Drivers and impacts of Eastern African rainfall variability. *Nat Rev Earth Env*,
 719 4(4): 254-270.
 720 Proctor, J., 2021. Atmospheric opacity has a nonlinear effect on global crop yields. *Nat Food*, 2(3):
 721 166-173.
 722 Qin, Y., 2021. Global competing water uses for food and energy. *Environ Res Lett*, 16(6): 064091.
 723 Ray, D.K., Gerber, J.S., MacDonald, G.K. and West, P.C., 2015. Climate variation explains a third of
 724 global crop yield variability. *Nat Commun*, 6: 5989.
 725 Raza, M.A., Gul, H., Yang, F., Ahmed, M. and Yang, W.Y., 2021. Growth Rate, Dry Matter
 726 Accumulation, and Partitioning in Soybean (L.) in Response to Defoliation under High -
 727 Rainfall Conditions. *Plants-Basel*, 10(8).
 728 Rigden, A.J., Mueller, N.D., Holbrook, N.M., Pillai, N. and Huybers, P., 2020. Combined influence of
 729 soil moisture and atmospheric evaporative demand is important for accurately predicting
 730 US maize yields. *Nat Food*, 1(2).
 731 Rosenzweig, C., Tubiello, F.N., Goldberg, R., Mills, E. and Bloomfield, J., 2002. Increased crop
 732 damage in the US from excess precipitation under climate change. *Global Environ Chang*,
 733 12(3): 197-202.
 734 SCIO, 2019. Food Security in China. In: S.C.I.O.o.t.P.s.R.o. China (Editor). State Council Information
 735 Office of the People's Republic of China, Beijing, pp. 10-14.
 736 Séférian, R. et al., 2019. Evaluation of CNRM Earth System Model, CNRM-ESM2-1: Role of Earth
 737 System Processes in Present-Day and Future Climate. *J Adv Model Earth Sy*, 11(12): 4182 -
 738 4227.
 739 Tao, F.L. et al., 2013. Single rice growth period was prolonged by cultivars shifts, but yield was
 740 damaged by climate change during 1981-2009 in China, and late rice was just opposite.
 741 *Global Change Biol*, 19(10): 3200-3209.
 742 Tatebe, H. et al., 2019. Description and basic evaluation of simulated mean state, internal variability,
 743 and climate sensitivity in MIROC6. *Geosci Model Dev*, 12(7): 2727-2765.
 744 Ting, M.F. et al., 2023. Contrasting impacts of dry versus humid heat on US corn and soybean
 745 yields. *Sci Rep-Uk*, 13(1).
 746 Togliatti, K., Archontoulis, S.V., Dietzel, R., Puntel, L. and VanLoocke, A., 2017. How does inclusion
 747 of weather forecasting impact in-season crop model predictions? *Field Crop Res*, 214:
 748 261-272.
 749 Trivedi, P., Anderson, I.C. and Singh, B.K., 2013. Microbial modulators of soil carbon storage:
 750 integrating genomic and metabolic knowledge for global prediction. *Trends Microbiol*,
 751 21(12): 641-651.
 752 Troy, T.J., Kipgen, C. and Pal, I., 2015. The impact of climate extremes and irrigation on US crop
 753 yields. *Environ Res Lett*, 10(5): 054013.
 754 Vain, S., Tamm, I., Tamm, Ü., Annusver, M. and Zobel, K., 2023. Negative relationship between
 755 topsoil root production and grain yield in oat and barley. *Agr Ecosyst Environ*, 349.
 756 van Erven, T. and Harremoës, P., 2014. Renyi Divergence and Kullback-Leibler Divergence. *Ieee T*
 757 *Inform Theory*, 60(7): 3797-3820.
 758 Wada, Y. et al., 2016. Modeling global water use for the 21st century: the Water Futures and
 759 Solutions (WFaS) initiative and its approaches. *Geosci Model Dev*, 9(1): 175-222.
 760 Wang, C.T. and Li, S.K., 2010. Assessment of Limiting Factors and Techniques Prioritization for
 761 Maize Production in China. *Scientia Agricultura Sinica*, 43(6): 1136-1146. (In Chinese with

762 English Abstract).

763 Webber, H. et al., 2020. No perfect storm for crop yield failure in Germany. *Environ Res Lett*, 15(10):

764 104012.

765 Xiao, F.J., Zhang, X.G., Liao, Y.M. and Liu, Q.F., 2020. Sunshine Duration in China: Variation

766 Characteristics and Its Influence. *Chinese Agricultural Science Bulletin*, 36(20): 92 -100. (In

767 Chinese with English abstract).

768 Xiao, H.B. et al., 2018. The mineralization and sequestration of organic carbon in relation to

769 agricultural soil erosion. *Geoderma*, 329: 73-81.

770 Xie, W. et al., 2023. Crop switching can enhance environmental sustainability and farmer incomes

771 in China. *Nature*, 616(7956): 300-305.

772 Yu, H.Y. et al., 2011. Variation Characteristics of the Sunshine Duration and Its Relationships with

773 Temperature, Wind Speed, and Precipitation over Recent 59 Years in China. *Climatic and*

774 *Environmental Research*, 16(3): 389-398. (In Chinese with English abstract).

775 Zhang, C., Dong, J.W. and Ge, Q.S., 2022. Mapping 20 years of irrigated croplands in China using

776 MODIS and statistics and existing irrigation products. *Sci Data*, 9(1): 407.

777 Zhang, Y.W., 2023. A study on the factors influencing the production security of major food crops

778 in China in the context of climate change, East China University of Political Science and

779 Law, Shanghai, China, 30-32 pp.

780 Zhu, B.W., Xie, X.H., Meng, S.S., Lu, C.Y. and Yao, Y., 2020. Sensitivity of soil moisture to

781 precipitation and temperature over China: Present state and future projection. *Sci Total*

782 *Environ*, 705: 135774.

783 Zhu, C.W. et al., 2023. Rising temperatures can negate CO₂ fertilization effects on global staple

784 crop yields: A meta-regression analysis. *Agr Forest Meteorol*, 342: 109737.

785 Zscheischler, J. et al., 2020. A typology of compound weather and climate events. *Nat Rev Earth*

786 *Env*, 1(7): 333-347.

787