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Summary

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Keywords: Climate Change Impacts, Crop Yields, Global Gridded Crop Models, ISI-MIP

JEL Classification: Q1, Q5

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Simulated vs. Empirical Weather Responsiveness of Crop Yields:

U.S. Evidence and Implications for the Agricultural Impacts of Climate Change

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Abstract

Global gridded crop models (GGCMs) are the workhorse of assessments of the agricultural impacts of climate change. Yet the changes in crop yields projected by different models in response to the same meteorological forcing can differ substantially. Through an inter-method comparison, we provide a first glimpse into the origins and implications of this divergence—both among GGCMs and between GGCMs and historical observations. We examine yields of rainfed maize, wheat, and soybeans simulated by six GGCMs as part of the Inter-Sectoral Impact Model Intercomparison Project-Fast Track (ISIMIP-FT) exercise, comparing 1981-2004 hindcast yields over the coterminous United States (U.S.) against U.S. Dept. of Agriculture (USDA) time series for about 1,000 counties. Leveraging the empirical climate change impacts literature, we estimate reduced-form econometric models of crop yield responses to temperature and precipitation exposures for both GGCMs and observations. We find that up to 60% of the variance in both simulated and observed yields is attributable to weather variation. Majority of the GGCMs have difficulty reproducing the observed distribution of percentage yield anomalies, and exhibit aggregate responses that show yields to be more weather-sensitive than in the observational record over the predominant range of temperature and precipitation conditions. This disparity is largely attributable to heterogeneity in GGCMs' responses, as opposed to uncertainty in historical weather forcings, and is responsible for widely divergent impacts of climate on future crop yields.

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Keywords: climate change impacts, crop yields, global gridded crop models, ISI-MIP

1. Introduction

Agriculture, particularly cultivation of field crops, is weather dependent and exposed to meteorological shifts (Gornall *et al* 2010, Moore and Lobell 2015), making it especially vulnerable to adverse effects of climate change (IPCC 2014). The specter of declining yields of maize, wheat, soybeans and other food staples with exposure to high temperature and low precipitation extremes arises from two lines of evidence (Moore and Lobell 2015, Lobell *et al* 2011, Porter *et al* 2014, Müller *et al* 2015, Lobell and Asseng 2017). First, the empirical climate change economics literature estimates reduced-form responses of yields to weather shocks using historically observed production, harvested area, temperature and precipitation in many locations across multiple years (e.g. Lobell *et al* 2011, Porter *et al* 2014, Schlenker and Lobell 2010, Tack *et al* 2015). Second, process-based crop models simulate the detailed influences on plant growth of a wide array of weather variables, plant genotypes, environmental factors such as the carbon dioxide (CO_2) fertilization effect (CFE), soil quality or pests, and agronomic adaptations such as irrigation, fertilizer application, and the timing of planting and harvesting (Elliott *et al* 2015, Bassu *et al* 2014, Rosenzweig *et al* 2014). Whereas the geographic domain of empirical studies is often limited to individual countries or regions with a sufficient number of historical observations,[1] global gridded crop models (GGCMs) simulate the growth of field crops worldwide under different climatic conditions projected by earth system models (ESMs) (see Deryng *et al* 2011, Rosenzweig *et al* 2014 and Elliott *et al* 2015 for further discussion), resulting in a comprehensive picture of the effects of climate change on crop yields.

Confidence in GGCMs' simulated agricultural impacts turns on the ability of models to accurately capture the myriad interacting meteorologically-driven processes that determine yields (Bassu *et al* 2014). GGCMs' representations of plant growth dynamics rely on numerous parameters that must be calibrated,

[1] For examples, see Iglesias *et al* 2000 for Spain, Lobell and Burke 2010 for U.S. counties, Lobell *et al* 2012 for India, Schlenker and Lobell 2010 for Sub-Saharan Africa.

but whose values are uncertain and may vary geographically in ways that are poorly constrained (Rosenzweig *et al* 2014, Jones *et al* 2016). Validation typically involves statistical evaluation of GGCMs' ability to reproduce point estimates of yields at different locations, for example at field trial sites or over spatially aggregated production regions under year-to-year variation in weather conditions (for excellent recent examples, see Morell *et al* 2016, Müller *et al* 2017). However, comparatively little attention has been paid to how the *response* of GGCMs-simulated yields to meteorological forcings compare with the weather sensitivity of yields observed in observed agricultural systems. Early studies focused on a single crop model (Lobell and Burke 2010; Watson et al 2015), and recent availability of extensive multi-model cross-section/time-series crop yields datasets generated by GGCM intercomparison exercises have facilitated reduced-form statistical emulation of single (Oyebamiji *et al* 2015) or multiple-GGCM (Blanc and Sultan 2015, Blanc 2017) simulations, for one or more crops (Blanc 2017). However, except for Lobell and Asseng 2017 and Schauberger *et al* 2017, such emulators do not appear to have been used for *diagnostic* purposes. It is this gap that we address here,[2] by comparing the responses of process simulations with those of econometric models trained on observations. Our strategy is to elucidate and compare the aggregate responses of observed and GGCM-simulated yields to observed and ESM-simulated temperature and precipitation under current climatic conditions. We pose six key questions:

Q.I How well do the outputs of GGCM hindcast simulations match historically observed yields?

Q.II Do GGCMs reproduce the correlations between yields and adverse (i.e., high temperature and low precipitation) weather extremes seen in the observational record?

Q.III How similar are GGCM-simulated and observed yield responses, under not only adverse extremes, but the full range of weather conditions over crops' growing seasons?

[2] Whereas Lobell and Asseng 2017 focus on identifying systematic differences between process-based and statistical methods, Schauberger *et al* 2017 address the yield losses in maize, soybeans and winter wheat (rainfed and irrigated) attributable to high-temperature induced mechanisms.

Q.IV Do differences between GGCMs and observations in the weather-responsive component of yields originate in divergent meteorological forcings (i.e., differences in temperature and precipitation exposures between weather observations and ESM historical simulations), versus divergence in GGCMs' simulated responses and observed crop responses to these forcings?

Q.V To which characteristics of GGCMs can the divergence between simulated and observed responses be attributed?

Q.VI What do simulated and observed response functions imply for the impacts of climate change-driven shifts in temperature and precipitation on future United States (U.S.) crop yields?

To provide answers we statistically extract and compare the responses of yield to weather shocks for two sets of data that span the same temporal and spatial domain: rainfed maize, wheat and soybeans in the coterminous U.S. over the period 1981-2004. For crop models we use the outputs of runs of six GGCMs fielded by the Inter-Sectoral Impact Model Intercomparison Project Fast-Track (ISIMIP-FT) exercise (Warszawski *et al* 2013, Rosenzweig *et al* 2014, Frieler *et al* 2015), together with their ESM-simulated meteorological forcings (Hempel *et al* 2013). For historical observations, we use U.S. Dept. of Agriculture (USDA) multi-decadal time series of production and harvested area for about 1,000 predominantly rainfed counties (whose areal extents are comparable to GGCMs' grid cells across U.S. farm states), matched to high-frequency temperature and precipitation exposures from a historical weather dataset.

The rest of the paper is organized as follows. Section 2 discusses our data and elaborates the methods we use to answer questions I-VI. A discussion of the results is provided in section 3. We summarize our findings with the associated caveats and recommendations for future research in section 4.

2. Methods

Our data consist of m unbalanced panel datasets of maize, wheat and soybean yields (Y) that are either observed or modeled at i areal units over t years, matched with observed or simulated daily temperature (T) and precipitation (P) over the growing season for the same locations and periods. Historical crop yields were computed from 1981-2004 county production and harvested area records from the USDA National Agricultural Statistics Service's Quickstats 2.0 database, which provides survey data.[3] Historical weather exposures are calculated from the Parameter-elevation Regressions on Independent Slopes Model (PRISM)[4] forcing files, which are daily meteorological fields on a 2.5 arcmin (~4 km) grid that we spatially interpolate to county boundaries. Simulated 1981-2004 yields on a 0.5° grid were taken from the ISMIP-FT ESGF node[5] for six GGCMs: GEPIC (Liu *et al* 2007), GAEZ-IMAGE (Bouwman *et al* 2006), LPJ-GUESS (Sitch *et al* 2003), LPJmL (BONDEAU *et al* 2007, Sitch *et al* 2003), pDSSAT (Elliott *et al* 2013, Jones *et al* 2003) and PEGASUS (Deryng *et al* 2011). Model runs are forced by historical bias-corrected meteorology simulated by the HadGEM2-ES climate model (Jones *et al* 2011) at the same resolution. Further details of the data and models are given in the Supplementary Information (SI).

Several factors complicate assessment of GGCMs' skill in reproducing the spatial and temporal patterns of observed yields (Q.I). GAEZ-IMAGE and LPJ-GUESS simulate potential yields while the remaining models simulate actual yields,[6] and models are calibrated using historical yields from different sources, whereas others are not calibrated (see Rosenzweig *et al* 2014 SI for further details). For consistency, we characterize the distribution of the differences between the cross-section/time-series yield anomalies of GGCMs ($m = g$) and observations ($m = USDA$), ${}^{*}Y_{i,t,GGCMs} - {}^{*}Y_{i,t,USDA}$. Anomalies are defined as fractional deviations from the de-trended long-run mean yield in each location, ${}^{*}Y_{i,t,g} = Y_{i,t,g}/\bar{Y}_{i,g} - 1$.

[3] http://quickstats.nass.usda.gov/ (accessed on 13 February 2017)

[4] PRISM daily data (1981~2004) accessed from http://www.ocs.orst.edu/prism/ on 13 February 2017

[5] https://esg.pik-potsdam.de/search/isimip-ft/

[6] Rosenzweig et al. 2014 define potential yields as "unlimited by nutrient or management constraints and without calibration of growth parameter to reproduce historical yields".

If ${}^{*}Y_{i,t,g}$ and ${}^{*}Y_{i,t,USDA}$ are similar, then we would expect the probability density function (PDF) of the anomaly difference to be sharply peaked at zero mean.

Our computed anomalies facilitate comparison of the covariation between yields and adverse weather (Q.II). Using a fixed annual growing season,[7] we calculate the days of each GGCM (USDA) grid cell's (county's) exposure to j intervals of temperature, ξ_j^T, and k intervals of precipitation, ξ_k^P (see Section S4). We then group grid cells by county, and for both simulations and observational datasets compute the county-level temporal correlations between de-trended yield, ${}^{*}Y_i$, and the extreme temperature and precipitation bins (j: T >30°C, k: P ≤5mm).

Taking this analysis one step further, we quantify the potentially nonlinear influence of climate on yields (Q.III) using a semi-parametric cross-section/time-series regression model, following the empirical climate-change impacts literature (Schlenker and Roberts 2006, 2009, Deschênes and Greenstone 2007, 2012, Lobell *et al* 2011, Ortiz-Bobea 2013, Wing *et al* 2015, Burke and Emerick 2016, Schauberger *et al* 2017). For each dataset we specify the dependent variable as the natural logarithm of annual yield (y), and the explanatory variables as a vector of location-specific effects (μ, which capture the influence of unobserved time-invariant local characteristics such as topography and soils), a time-varying function, $f(t)$, which captures the influence of unobserved time-varying shocks, and the vectors of weather exposure covariates ξ_j^T and ξ_k^P described above, and append a random disturbance term, ε:

$$y_{i,t,m} = \mu_i + f(t) + \Sigma_j \beta_{j,m}^T \xi_{j,i,t}^T + \Sigma_k \beta_{k,m}^P \xi_{k,i,t}^P + \varepsilon_{i,t,m} \quad (1)$$

We estimate eq. (1) via ordinary least squares on the observational dataset of USDA yield and PRISM weather, the six datasets of GGCM yield outputs and ESM weather inputs, and multi-model panel

[7] For both simulated and historical datasets, we define the growing season as April-August (AMJJA) for wheat and May-August (MJJA) for maize and soybeans. See SI for details.

consisting of the combined inputs and outputs of the six GGCMs.[8] Specifying the function $f(\cdot)$ involves tradeoffs in temporal and spatial flexibility: time effects ($f(t) = \tau_t$) capture the secular influence of year-to-year shocks common to all counties, while geographic variation in trending influences (e.g., input prices, technology adoption, management practices) can be captured by state-specific linear time trends ($f(t) = \lambda_s t$).[9]

Of interest in eq. (1) are the estimated parameters $\boldsymbol{\beta}_m^T$ and $\boldsymbol{\beta}_m^P$, vectors of semi-elasticities that capture the average percentage shift in county-level ($m = USDA$) and grid-level ($g \in m$) yields relative to their conditional mean quantities in response to an additional day in a given interval of temperature or precipitation. Each element of these vectors captures the marginal effect of an additional day of exposure within the corresponding interval (e.g., the average effect of one more day with $25 - 27°C$ versus $> 30°C$ average temperature). Together, the elements flexibly trace out the aggregate response of yields to temperature and precipitation as piecewise linear splines. The latter are statistically identified from the contemporaneous covariation between observed yields and meteorology within each interval, as well as the distribution of temperature and precipitation exposures across intervals in our transformed datasets.

Empirically-derived yield responses from the GGCM-ESM and USDA-PRISM datasets are not directly comparable because they are based on different meteorological inputs with distinct exposure distributions: ESM-simulated $\xi_j^{T,ESM}$ and $\xi_k^{P,ESM}$ versus observed $\xi_j^{T,PRISM}$ and $\xi_k^{P,PRISM}$. This raises the question of whether differences between the fitted GGCM-ESM and USDA-PRISM semi-elasticities ($\widehat{\boldsymbol{\beta}}_g^T - \widehat{\boldsymbol{\beta}}_{USDA}^T$ and $\widehat{\boldsymbol{\beta}}_g^P - \widehat{\boldsymbol{\beta}}_{USDA}^P$) are simply the product of differences in the distributions of temperature and

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[8] The multi-model econometric specification generates multi-model average responses, $\overline{\boldsymbol{\beta}}^T$ and $\overline{\boldsymbol{\beta}}^P$, controlling for variation among GGCMs via a model-specific indicator, γ:

$$y_{i,t,g} = \mu_i + \gamma_g + f(t) + \Sigma_j \overline{\beta}_j^T \xi_{j,i,t}^T + \Sigma_k \overline{\beta}_k^P \xi_{k,i,t}^P + \varepsilon_{i,t,g}.$$

[9] The specification estimated using USDA data uses a state-specific time trend. While the ISIMIP-FT protocol requires management practices and technology to be held constant at year 2000 levels, different GGCMs include a variety of endogenous adaptation mechanisms (see Section 3.5). We therefore consider a model with time effects more appropriate. For comparability, we also tested a specification for GGCMs using state-specific time trends as opposed to time effects (results available upon request). Results hold across different specifications.

precipitation inputs to yields (Q.IV). From (1), the weather-responsive component of log yield is defined as:

$$\psi_m(\boldsymbol{T}_i, \boldsymbol{P}_i) = \Sigma_j \hat{\beta}^T_{j,m} \xi^T_{j,i} + \Sigma_k \hat{\beta}^P_{k,m} \xi^P_{k,i} \tag{2}$$

and the difference between the weather-responsive components of GGCM and USDA yield is thus

$$\Delta\psi_g = \psi_g(\boldsymbol{T}_i, \boldsymbol{P}_i) - \psi_{USDA}(\boldsymbol{T}_i, \boldsymbol{P}_i) = \Sigma_j \hat{\beta}^T_{j,g} \xi^{T,ESM}_{j,i} + \Sigma_k \hat{\beta}^P_{k,g} \xi^{P,ESM}_{k,i}$$
$$- \left(\Sigma_j \hat{\beta}^T_{j,USDA} \xi^{T,PRISM}_{j,i} + \Sigma_k \hat{\beta}^P_{k,USDA} \xi^{P,PRISM}_{k,i}\right) \tag{3}$$

Adding and subtracting cross-terms on the right-hand side of eq. (3) and evaluating the weather exposure covariates at their 1981-2004 climatic means facilitates decomposition of $\Delta\psi$ into two terms, one capturing the effect of differences in climate forcing and the other capturing the effect of differing responses to meteorology:

$$\Delta\psi_g = \underbrace{\Sigma_j \hat{\beta}^T_{j,g} \left(\bar{\xi}^{T,ESM}_{j,i} - \bar{\xi}^{T,PRISM}_{j,i}\right) + \Sigma_k \hat{\beta}^P_{k,g} \left(\bar{\xi}^{P,ESM}_{k,i} - \bar{\xi}^{P,PRISM}_{k,i}\right)}_{\text{Climate component } (\Delta\psi^{Climate})}$$
$$+ \underbrace{\Sigma_j \left(\hat{\beta}^T_{j,g} - \hat{\beta}^T_{j,USDA}\right) \bar{\xi}^{T,PRISM}_{j,i} + \Sigma_k \left(\hat{\beta}^P_{k,g} - \hat{\beta}^P_{k,USDA}\right) \bar{\xi}^{P,PRISM}_{k,i}}_{\text{Response component } (\Delta\psi^{Response})} \tag{4}$$

The relative importance of $\Delta\psi^{Climate}$ and $\Delta\psi^{Response}$ can then be assessed by comparing their distributions across locations.

Eq. (1)'s estimated parameters enable us to investigate another key question: how do the characteristics of models drive the divergence between GGCM yield responses and those of historical yields to observed weather (Q.V). Drawing on documentation for each of our six GGCMs (Rosenzweig *et al* 2014, Elliott *et al* 2015), we construct binary indicator variables for five sets of characteristics likely to affect the yield response: (i) type of yield simulated (actual versus potential); (ii) endogenous cultivar change; (iii) heat stress; (iv) endogenous sowing date; (v) and whether the model was calibrated using site-specific or FAO country observations (Table S6). We assemble characteristics (i)-(v) into a matrix, **Z**. Then, using the stacked vector of temperature and precipitation semi-elasticities ($\zeta_m = \left[\widehat{\boldsymbol{\beta}}^T_m, \widehat{\boldsymbol{\beta}}^P_m\right]$) we compute the difference in the response from the USDA benchmark, $\Delta\zeta_g = \zeta_g - \zeta_{USDA}$, which we employ as the dependent variable in the meta-analysis regression:[10]

$$\Delta\zeta = \boldsymbol{Z}\,\boldsymbol{\eta} + \nu \quad (5)$$

The estimated parameters, η, indicate how strongly the shift in GGCM-ESM responses relative to the USDA-PRISM response is associated with each model attribute.

Finally, the implications of our estimated responses for future climate change impacts (Q.VI) are indicated by the yield changes that result from forcing our fitted empirical response functions with the distributions of temperature and precipitation under future climate warming. Log yield response functions from eq. (2) are combined with meteorological exposures from bias-corrected HadGEM2-ES model simulations for our hindcast period (current climate), as well as mid-21st century (2033-2065) and late century (2067-2099) future climate under the RCP 8.5 (Moss *et al* 2010) high-warming scenario. In each epoch HadGEM2-ES daily temperature and precipitation ($\widetilde{\boldsymbol{T}}_i$ and $\widetilde{\boldsymbol{P}}_i$) fields are binned into the j and k intervals, respectively, to construct analogues of the weather exposure covariates, $\tilde{\xi}^T$ and $\tilde{\xi}^P$, for current and future years. Because climate simulations do not reproduce observed high-frequency weather extremes, and may exhibit biases relative to current climate (Vavrus *et al* 2015, Schoof and Robeson 2016), we do not directly compare simulated future exposures against their observed counterparts, but instead employ the "delta" change method of computing differences in exposure between ESM-simulated current and future climates.[11] Specifically, we time-average the temperature and precipitation bins to generate the mean meteorological exposure for the hindcast period (current climate), calculate the difference between the resulting average and simulated exposure under future climate, and finally

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[10] This model is estimated with no constant. We test additional specifications to investigate both the impacts of model characteristics on the differences in responses to temperature and precipitation alone ($\zeta_m = \widehat{\boldsymbol{\beta}}_m^T$ and $\zeta_m = \widehat{\boldsymbol{\beta}}_m^P$, respectively), as well as the effects of interactions between characteristics and indicators of extreme high temperature and low precipitation.

[11] First studies using this method include Arnell (1996) and Gleick (1986). For application of this method in the context of agriculture see (Roberts *et al* 2013).

multiply the result by the estimated semi-elasticities to generate meteorological shocks to log yields. We use the latter to compute a normalized multi-decadal index of climate impact, given by the ratio of each location's average yield under a future climate to its average yield under the present climate. Using $\mathbb{E}$ to denote the expected value over each epoch, the index is:

$$\Psi_{i,m} = \mathbb{E}\left[\exp\left\{\psi_m\left(\widetilde{\boldsymbol{T}}_i^{\substack{Future\\Climate}}, \widetilde{\boldsymbol{P}}_i^{\substack{Future\\Climate}}\right) - \psi_m\left(\widetilde{\boldsymbol{T}}_i^{\substack{Current\\Climate}}, \widetilde{\boldsymbol{P}}_i^{\substack{Current\\Climate}}\right)\right\}\right] \quad (6)$$

We note that Ψ_i diverges from fractional changes in future yields from the current climate projected by GGCMs, as eq. (6) omits both the CFE and endogenous adaptation mechanisms into GGCMs models, particularly endogenous or unrecorded prescribed future changes in fertilizer application rates, crop calendars, or crop genotypes.[12]

3. Results

3.1. GGCMs' ability to reproduce recorded yields

Fig. 1 summarizes the distributions of the differences in percentage yield anomalies between GGCMs and USDA records for our three crops over the 1981-2004 period. The wide support of the distribution suggests that the ISIMIP-FT GGCMs struggle to reproduce the PDF of historical U.S. yield anomalies. For counties within the interquartile range the GGCM-observation divergence is -/+30%, while in the majority of remaining locations simulated yields can dramatically overstate or understate the observations.

While this pattern persists across crops, GGCMs' performance—as indicated by the variance of the distributions—is generally better for wheat and especially maize compared to soybeans. The modes of the individual annual cross-county PDFs (shown in light colors) exhibit positive and negative interannual fluctuations, but do not follow any easily discernible pattern that suggests systematic bias. The differences

[12] For instance, see Rosenzweig *et al* 2014 SI for details on adaptations accounted for by the GGCMs, and Elliott *et al* 2015 for revised protocols in the next phase of GGCMs' simulations to introduce harmonization in GGCMs' simulation runs.

across models and among crops in the annual and aggregate PDFs also suggest that no single GGCM has a clear advantage in modeling all crops.[13] A certain GGCM may exhibit skill in modeling a particular crop (e.g., LPJmL wheat), while some GGCMs outperform others in simulating a certain crop (e.g., GAEZ-IMAGE versus GEPIC for maize).

[13] GAEZ-IMAGE appears to be an exception, perhaps due to its unique temporal scale relative to other GGCMs—interpolating monthly meteorology to a daily time-step, while simulating annual yields every 5th year and interpolating yields for the intervening years (Rosenzweig *et al* 2014: Table S4).

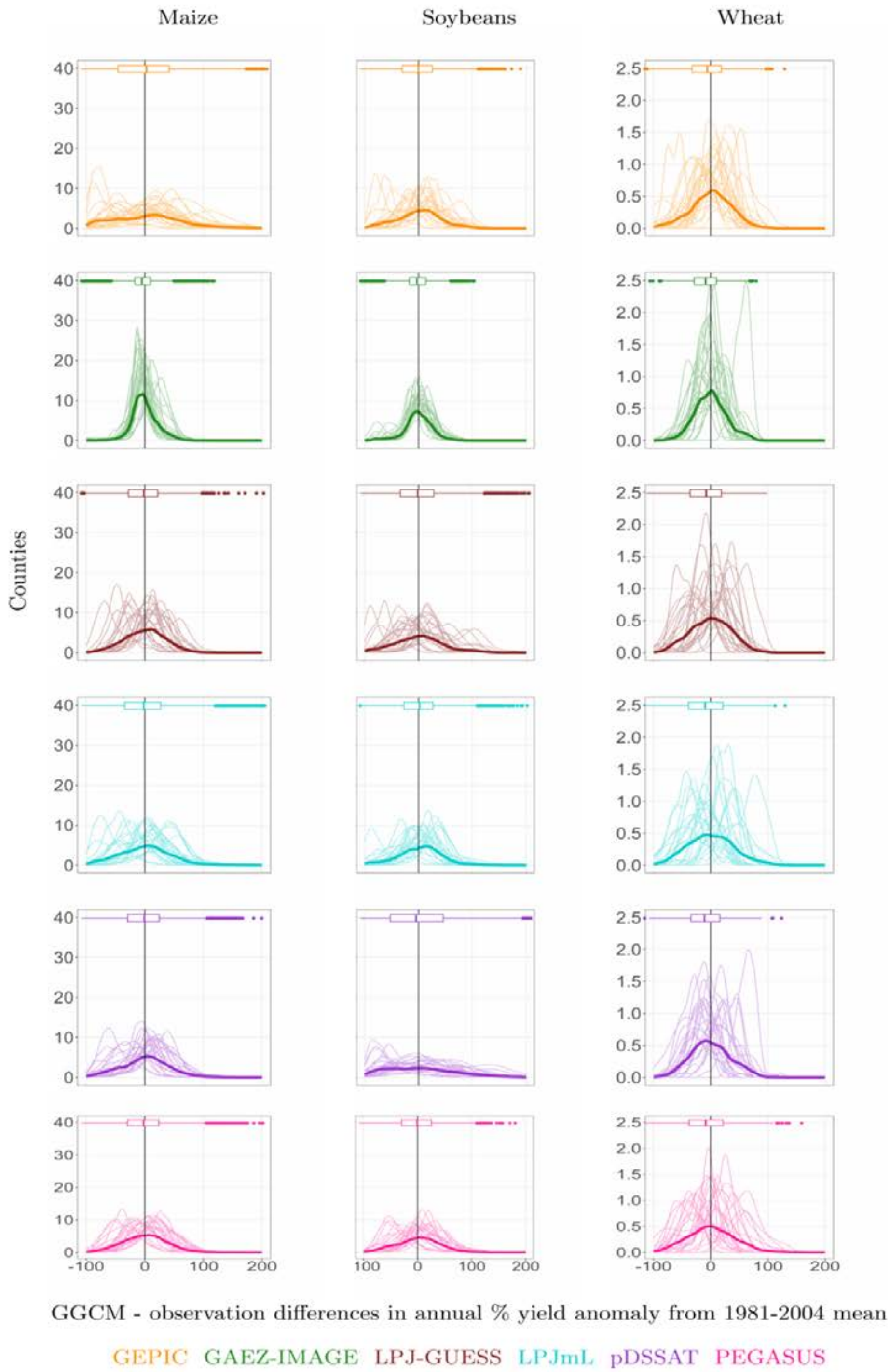

Fig. 1. Cross-county distribution of the GGCM - USDA difference in percentage yield anomalies for maize, soybeans, and wheat. Anomalies are calculated as the % deviation of each county's de-trended yield from its own 1981-2004 mean. Light lines show the annual distribution of county differences between each model and observations. Heavy lines show the distribution across counties and years.

3.2. Yield correlations with adverse weather extremes: simulations vs. observations

A more nuanced way to evaluate GGCMs' performance is to examine how well they reproduce historical correlations between annual yield anomalies and exposure to extreme high temperature and low precipitation. We do this in Fig. 2 by presenting the correlations between de-trended yields and annual growing season exposures to extreme high temperature and extreme low precipitation bins as a bivariate PDF. Relative to our comparison of yield anomalies (Section 3.1), there is more agreement in correlations between ESM-simulated meteorological extremes and GGCM-simulated yields, and the correlations between PRISM meteorological extremes and observed yields. Both correlations are negative in 50-75% of counties (with the exception of GAEZ-IMAGE), and the magnitudes of the correlations differ both across models and among crops. Simulated maize and soybean responses are for the most part qualitatively similar to observations, with GEPIC, LPJ-GUESS, LPJmL showing tight clustering of negative correlations across counties. Even so, simulated wheat responses vary markedly relative to one another, and diverge from observations. This result may arise from GGCMs simulating different types of wheat (e.g., GGCMs decide internally the type of wheat to be grown) while our observational data are spring durum wheat only.

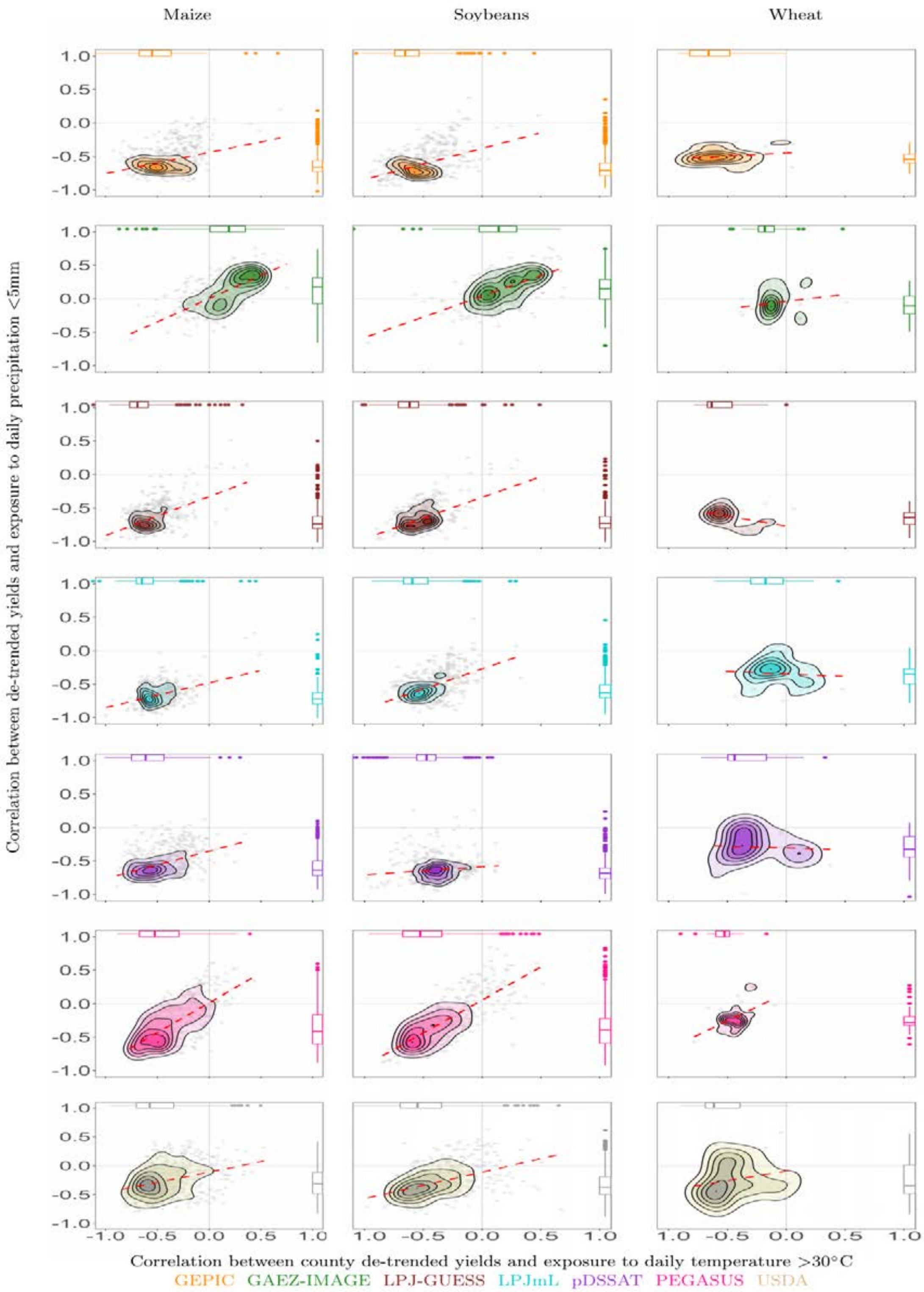

Fig. 2. Correlations between de-trended yields and extreme high temperature exposures (horizontal axis) and extreme low precipitation exposures (vertical axis) for six GGCMs and observations. Dashed red lines are the linear fit indicating the cross-county pattern of association between temperature and precipitation exposure correlations.

3.3. Simulated and observed yield responses to weather

In a refinement of the analysis in Section 3.2 we statistically model additional factors that affect yield. One is management practices, whose sub-national and interannual variation is unfortunately not available in either the GGCM-ESM or USDA-PRISM datasets. Another is non-extreme weather: negative yield impacts of more frequent extreme low precipitation and/or high temperature days might be offset by near-optimal growing conditions throughout the remainder of the growing season, while yields may be lower in counties and years that experience fewer extreme adverse days, but more frequent non-extreme but nonetheless sub-optimal weather.

Eq. (1) accounts for both sets of factors by partitioning the variance in yields into influences associated with unobservables (μ_i and $f(t)$) and the mean deterministic effects of the distribution of temperature and precipitation conditions experienced by crops. Fig. 3 illustrates the splines tracing out the responses of log yield to the distribution of temperature and precipitation. All covariates explain 75% of the cross-section/time-series yield variation (Table S4), and the weather responses account for between 0% and 60% (Table S5). GGCM and USDA yield responses are both consistent with empirical findings on the negative effects of exposure to high daily temperatures and (aside from GEPIC maize and pDSSAT soybean simulations) as well as smaller magnitude responses to low precipitation (cf. Schlenker and Roberts 2009, Tack *et al* 2015).

Whether the responses of different GGCMs to both extreme and non-extreme weather vary can be said to diverge from one another (panels A-C and G-I), and from the USDA-PRISM benchmark (panels D-F and J-L) depends on the specification of the variance-covariance matrix of the error term in eq. (1). Our default standard errors are clustered at the level of cross-sectional units (counties in the case of USDA-PRISM and grid-cells in the case of GGCMs) and are robust to temporal autocorrelation. They suggest differences in responses among individual GGCMs, and between GGCMs and USDA-PRISM that are statistically significant (Table S8). However, in empirical models of crop yields, residual spatial autocorrelation can substantially inflate the standard errors of the coefficients (Yun et al, 2015). Adjusting for joint residual temporal and spatial autocorrelation using Cameron-Gelbach-Miller (2011) clustering of the standard errors by county/cell and year increases their values by factors of 2-3 (Table S4), weakening the conclusion that the GGCM and USDA-PRISM responses significantly diverge—especially in the case of extreme high-temperatures (cf. Schauberger et al, 2017), but less so for extreme low precipitation (Table S8). Even so, for either specification of the variance-covariance matrix, no GGCM exhibits a consistent positive or negative bias relative to the USDA-PRISM response.

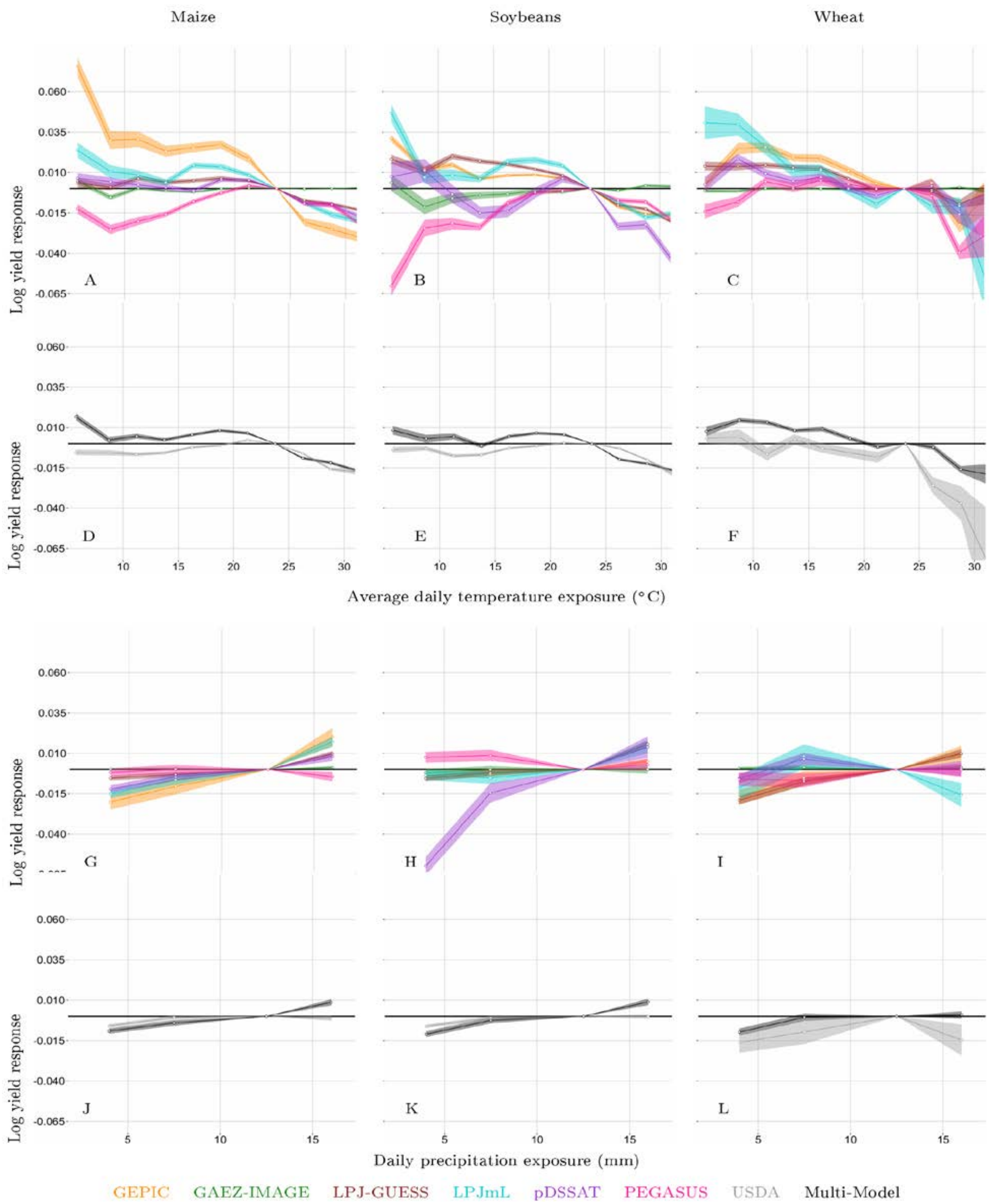

Fig. 3. Mean responses (solid lines) and confidence intervals (95%) (shaded areas) of log yield to temperature and precipitation exposure for maize, soybeans and wheat (eq. 1). Responses are normalized relative to the number of days with temperatures $22.5 - 25°C$ and precipitation $10 - 15\ mm/day$, represented by the heavy horizontal axis. Shaded confidence intervals are computed from robust standard errors clustered at the county/grid cell level.

The USDA-PRISM response suggests that exposure to an additional day >30°C reduces annual maize and soybean yields by 1.5% but generates wheat yield losses six times as large. For GGCMs, the corresponding response varies between 0.2-3% for maize, 0.5-3.6% for soybeans, and 0.1-6.5% for wheat, and the observed responses fall within the range of simulated responses, except for wheat. Exposure to an additional day with precipitation <5 mm reduces maize and soybean yields by about 0.5% and wheat by about 1.5% in the observational dataset. GGCMs exhibit larger losses for maize and soybeans (with the exception of PEGASUS), between 0 and 4.5% (1% at the multi-model average response), whereas wheat's response to dry days in the observational dataset is understated by most models (with the exception of GEPIC and LPJmL).[14]

3.4. Decomposition of the divergence between GGCM and USDA yield responses

We focus on two factors that likely drive the GGCM-observation divergence in Fig. 3.[15] The first is differences between the aggregate responses to weather shocks implied by process models' internal representation of crop growth and the responses of observed agricultural systems. The second is differences in the exposures implied by the PRISM data for the observations as opposed to HadGEM2-ES for the GGCMs. We use the decomposition technique illustrated in eq. (4) to establish their relative magnitudes. Fig. 4 shows the results of this calculation.

The horizontal axis rank-orders counties from the largest negative to the largest positive values of the difference between the weather-responsive portion of each GGCM's historical run and the observations, $\Delta\psi$, whose magnitude is measured on the vertical axis and whose county values are indicated by black dots. For each county the corresponding light- and dark-colored bars indicate the response and climatic

[14] The econometric models for simulated wheat generally have a lower explanatory power compared to maize and soybeans (see table S5). This might be due to differences in the type of wheat chosen by models compared to the variety observed, spring durum wheat) and to the fact that those varieties might be grown outside the growing season (April-August), see also section S5 in SI.

[15] A potential third issue is omitted variable bias, in the form of contaminating effects on the estimated parameters of management practices that are correlated with weather and unrecorded in the observational dataset, but omitted from GGCM simulations.

components of the divergence ($\Delta\,\psi^{Response}$ and $\Delta\,\psi^{Climate}$, respectively). For the majority of GGCM x crop combinations, cross-county trends in the total divergence and $\Delta\,\psi^{Response}$ closely track one another, while $\Delta\,\psi^{Climate}$ tends to add either noise or an offset. This result demonstrates that the differences in the splines in Fig. 3 are mostly attributable to GGCMs' internal responses, not differences in meteorological inputs.

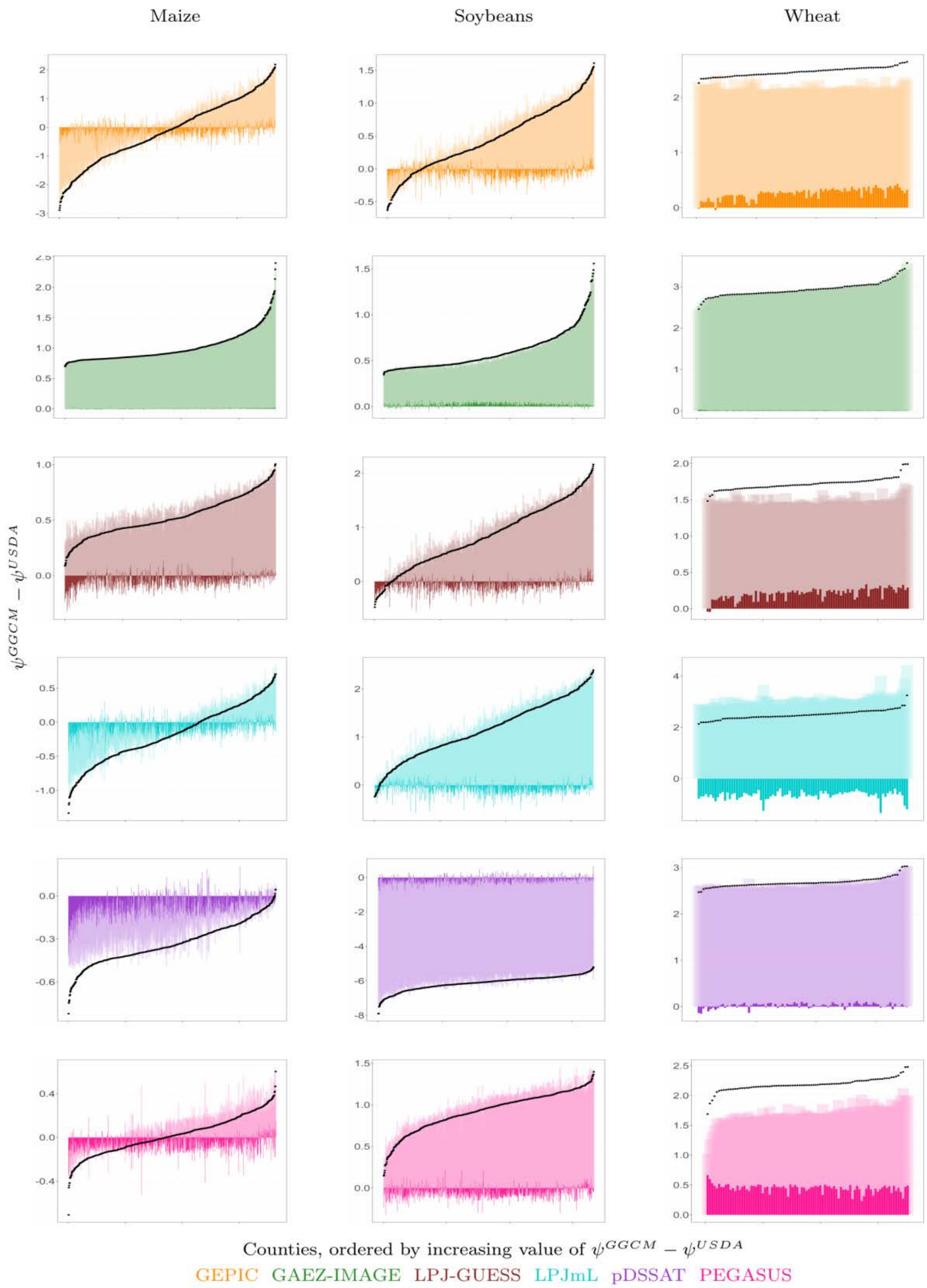

Fig. 4. Decomposition of predicted weather component of GGCM yield - predicted weather component of observed yield for counties (about 730 for maize, 670 for soybeans, 88 for wheat) showing the total difference (black line), climate component (dark bars), and response component (light bars).

3.5. Correlates of the GGCM-USDA yield response divergence

Finally, Table 1 summarizes our meta-analytic results that associate model attributes with the gaps between GGCMs' responses and those derived from historical observations. To conserve space we report results for maize only, and consign results for wheat and soybeans to the SI (Table S7). The largest magnitude coefficient is on heat stress, whose overall impact is to make the divergence in responses the more negative, suggesting that in panels A and G of Fig. 3, the responses of the sole model incorporating this mechanism (PEGASUS) exhibits a smaller change in yield (i.e., a downward shift) for an additional day of exposure over their entire range of weather variation. Simultaneously, the positive effect of heat stress interacted with high-temperature (low-precipitation) intervals indicates that in panel A (G) the right (left) tails of the corresponding splines are shifted upward, resulting in a less weather sensitive—i.e., flatter—response profile. Cultivar adaptation, the second largest influence, acts in the opposite way: inducing an upward shift in the response profiles over their entire range that is outweighed by the negative impact of interactions with extreme high temperature and low precipitation exposures, resulting in a more weather sensitive—i.e., steeper—profile for models that include this mechanism (GEPIC, and less evident for LPJ-GUESS, PEGASUS). Other characteristics, such as endogenous selection of sowing dates and model calibration based on site-specific studies—which respectively flatten and steepen the response profiles, have a smaller overall influence and are not uniformly significant across all crops. The major implication is that with a flatter response profile, shifts in the distributions of temperature and precipitation inputs translate into smaller simulated yield changes, while a steeper response profile can result in excess sensitivity that translates modest weather shocks into large yield changes.

Table 1: Effects of model characteristics on GGCM-USDA divergence in maize yield response. Model specifications are discussed in the SI. Robust standard errors in parentheses. Table S7 summarizes results for soybeans and wheat.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$\Delta\zeta[\widehat{\beta}^P, \widehat{\beta}^T]$	$\Delta\zeta[\widehat{\beta}^T]$	$\Delta\zeta[\widehat{\beta}^P]$	$\Delta\zeta[\widehat{\beta}^P, \widehat{\beta}^T]$	$\Delta\zeta[\widehat{\beta}^T]$	$\Delta\zeta[\widehat{\beta}^P]$
Potential yield	-0.007	-0.011	0.004	-0.024***	-0.028***	-0.015***
	(0.008)	(0.009)	(0.010)	(0.008)	(0.008)	(0.004)
Endog. cultivar	0.013	0.017*	-0.001	0.033***	0.036***	0.021
	(0.008)	(0.010)	(0.010)	(0.008)	(0.008)	
Endog. sowing date	-0.0003	-0.0004		-0.005***	-0.005**	
	(0.002)	(0.002)		(0.002)	(0.002)	
Heat stress	-0.017**	-0.023**	0.001	-0.035***	-0.040***	-0.025
	(0.008)	(0.009)	(0.010)	(0.008)	(0.008)	
Site calibration	0.004**	0.005***		0.007***	0.005***	
	(0.002)	(0.001)		(0.001)	(0.002)	
$T > 30°C$						
× Potential yield				0.051***	0.059***	
				(0.009)	(0.009)	
× Endog. cultivar				-0.056***	-0.063***	
				(0.009)	(0.009)	
× Endog. sowing date				0.015***	0.015***	
				(0.004)	(0.004)	
× Heat stress				0.048***	0.056***	
				(0.009)	(0.009)	
× Site calibration				-0.006**		
				(0.003)		
$P < 5$mm						
× Potential yield				0.035***		0.028***
				(0.008)		(0.005)
× Endog. cultivar				-0.044***		-0.033***
				(0.008)		(0.002)
× Endog. sowing date				0.010***		
				(0.003)		
× Heat stress				0.044***		0.039***
				(0.008)		(0.002)
× Site calibration				-0.012***		
				(0.002)		
F Adj.	4.289***	4.885***	1.553	42.577***	24.052***	2.325*
	(df = 4;77)	(df = 4;59)	(df = 2;17)	(df = 14;77)	(df = 8;59)	(df = 5;17)
Obs.	78	60	18	78	60	18
Adj. R Sq.	0.211	0.308	-0.153	0.593	0.624	0.336

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

We obtain broadly similar results for soybeans, but equivocal estimates for wheat (table S7), whose response is positively affected by heat stress interacted with low precipitation intervals, capturing the PEGASUS model's flatter response to precipitation relative to the other GGCMs.

While the source of this disparity is not clear cut, we speculate that it emanates from inter-model variation in the type of wheat being grown, and emphasize that our meta-analytic approach will likely prove more beneficial in imminent intercomparison exercises with comprehensive records (e.g., ISI-MIP2 and Global Gridded Crop Model Intercomparison, Elliott *et al* 2015).

4. Discussion and Conclusions

Using cross-section/time-series datasets of simulated and observed rainfed yields of maize, wheat and soybeans for about1,000 U.S. counties over 24 years, we have characterized the heterogeneous responses of crop models to ESM-simulated temperature and precipitation, and compared them with empirically derived responses to observed weather series. The six GGCM simulations we examined do not reproduce the cross-county, inter-annual distributions of yield. Notwithstanding this, our econometric analyses indicate that GGCM broadly capture the major stylized facts of weather impacts on crop yields that have been identified by the empirical climate change economics literature. Yet the responses of individual GGCMs differ substantially from one another and relative to their observationally-derived counterpart. Simulated yields are generally more temperature sensitive than observed yields, but can more or less sensitive to high temperature or low precipitation extremes, depending on the particular model and crop. We show that such behavior is attributable to differences in how models simulate heat stress and cultivar adaptation. GGCMs incorporating the latter (former) mechanism tend to be more (less) sensitive to weather shocks.

The consequences of these details for the impacts of climate change on U.S. crops are summarized in Fig. 5. The yield changes therein are calculated not by running GGCMs with meteorological inputs projected by ESMs, but by forcing their response functions derived in Fig. 3 with changes in future temperature and precipitation exposures from the historical period simulated by HadGEM2-ES. They therefore do not account for the potential benefits of the CFE, or future management changes and other adaptations either endogenously computed by, or exogenously imposed upon, GGCMs simulations as part of the ISIMIP-FT exercise. Notwithstanding the overlap in the confidence intervals of the GGCMs' responses, under vigorous warming, late-century (2067~2099) projections of production changes based on the coefficient point estimates diverge widely; ranging from -96% to +6%—and -71% at the multi-model mean response—for maize, -90% to +21% with a mean of -70% for soybeans, -91% to -1% with a mean of -70% for wheat. The responses of GGCMs that are most sensitive to extreme high temperatures (GEPIC, LPJ-GUESS and LPJmL) are associated with the largest losses, in excess of 40% of maize and wheat production, and 60% of soybean production by mid-century (2033~2065), while only GAEZ-IMAGE predicts production gains. Relative to the GGCM responses, our USDA-PRISM response generates smaller losses (-58% for maize, -60% for soybeans, -90% for wheat) for late-century, but its predicted production declines due to more frequent days $> 30°C$ closely track those reported by Schauberger *et al* (2017)[16] for the $30°C - 36°C$ temperature range (-54% for maize, -60% for soybeans and -73% for wheat—see Table S9) which gives us confidence in the reliability of our approach[17].

[16] While a direct comparison with results of Schauberger *et al* (2017) is difficult to make for maize and soybeans (due to a larger number of counties utilized in their study), results for wheat are not comparable due to winter wheat used in their study.

[17] By contrast, GGCMs' late century (2067~2099) losses due to extreme high temperature days ($> 30°C$), range from -72% to +3%—and -53% at the multi-model mean—for maize, -86% to +7% with a mean of -56% for soybeans, and -66% to -4% with a mean of -42% for wheat.

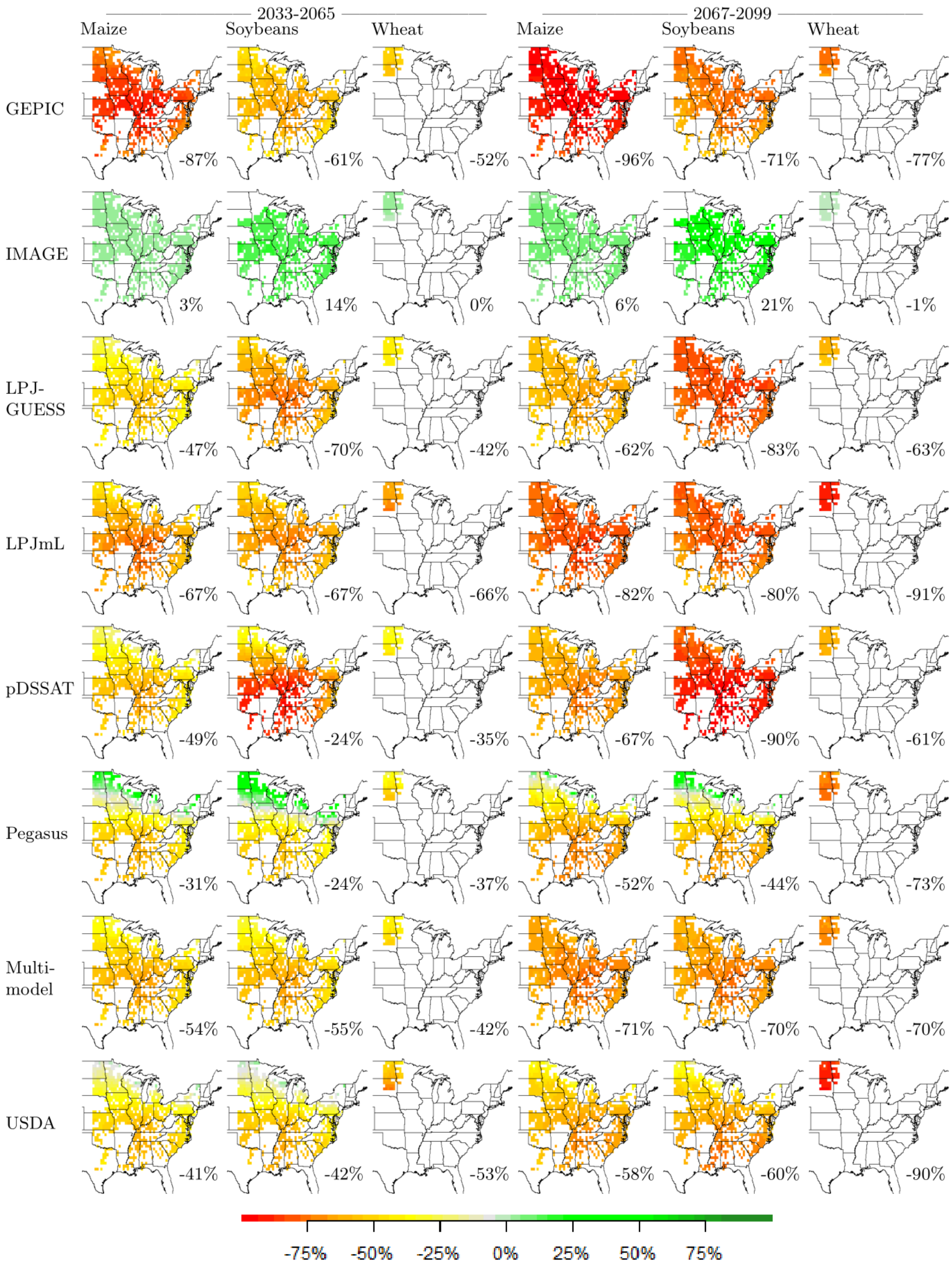

Fig. 5. Mid- and end-century % change in rainfed yields under RCP 8.5 warming scenario simulated by HadGEM2-ES. The % change numbers accompanying each map depict the projected % change in aggregated production across the sample of counties, under the assumption of same harvested area in future periods, as in historical.

By relying solely on meteorological inputs, and ignoring confounding factors such as the CFE, exogenous future adaptations or additional endogenous adjustments such as shifts in cultivars and crop calendars represented within models, our projections provide insights into how GGCMs' characteristics can amplify or moderate climatically-driven yield declines. For example, a key feature of Fig. 5 is the lack of spatial (particularly latitudinal) variation in GGCM yield shocks compared to the USDA projections. The exception is the PEGASUS model, whose flatter response profiles generate smaller losses than the USDA benchmark. For most of the remaining GGCM responses the converse is true: excess sensitivity generates yield changes—and, without compensating adaptation mechanisms, production losses—that are uniformly large. Heat stress at anthesis (and, secondarily, endogenous sowing) may therefore be important for bringing models' overall sensitivity into better agreement with the responses exhibited by observed agricultural systems. But this also raises the question of what model attributes might drive GGCMs' excess sensitivity. Our findings hint at endogenous cultivar selection as a potential candidate, as it amplifies negative yield responses to low precipitation in soybeans, high temperature in wheat, and both types of weather shocks in maize. Another may be the use of site-specific data for calibrating maize and soybean simulations, but the potential mechanisms are unclear.

Such interpretation challenges highlight four important caveats to our analysis. The first is the small number of observations on which our meta-analysis results are based, especially relative to the number of dimensions along which GGCMs can potentially vary. Without a larger sample of models, little can be done to increase the statistical power of our assessment. A second, related issue is that because the ISIMIP-FT protocol did not mandate standardization of GGCMs' characteristics, or harmonization and recording of the corresponding detailed inputs across models and scenarios, our own coding of model attributes could conceivably introduce errors. Third, the aforementioned paucity of data required us to use all of the parameters of the GGCM and USDA-PRISM estimated responses, as opposed to zeroing out differences that were not statistically significant. With the latter approach, the substantial reduction in the divergence between GGCM- and observationally-based responses when residual spatial autocorrelation is accounted for can potentially weaken our inferences in Table 1. Finally, because the GGCM simulations employed here are not specifically optimized for US counties, it is not clear how well our results extrapolate beyond the specific spatial domain of the eastern US.

All of these limitations are already being addressed by the current generation of crop model inter-comparison exercises (ISI-MIP2, the Global Gridded Crop Model Intercomparison (Elliott *et al* 2015)), which are in the process of fielding larger numbers of GGCMs running more controlled experiments with considerable efforts being made to harmonize and record key inputs such as management practices, and evaluate model outputs against a common set of recently-developed global historical data benchmarks (Ray *et al* 2012, Iizumi *et al* 2014). Our hope is that the inter-method comparison techniques developed here can contribute to improving the evaluation of the results of these exercises (cf Müller *et al* 2017), with the goals of more rigorously pinpointing the origins of GGCMs' emergent crop yield responses, and thereby strengthening the empirical basis of global-scale assessment of future climate change impacts on agriculture.

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Supplementary Information

Simulated vs. Empirical Weather Responsiveness of Crop Yields:

U.S. Evidence and Implications for the Agricultural Impacts of Climate Change

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S1. Global Gridded Crop Models (GGCMs) from ISIMIP-Fastrack used in this study along with the contact details of the modelling groups

(i) Geographic Information System (GIS)-based Environmental Policy Integrated Climate (GEPIC) (Liu *et al* 2007)

(ii) Global Agro-Ecological Zone model in the Integrated Model to Assess the Global Environment (GAEZ-IMAGE) (Van Vuuren *et al* 2006)

(iii) Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) (Bondeau *et al* 2007)

(iv) Lund Potsdam-Jena managed Land (LPJmL) (Bondeau *et al* 2007, Sitch *et al* 2003)

(v) parallel Decision Support System for Agro-technology Transfer (pDSSAT) (Elliott *et al* 2013, Jones *et al* 2003)

(vi) Predicting Ecosystem Goods And Services Using Scenarios (PEGASUS) (Deryng *et al* 2011)

Table S1. GGCMs used in this study, with the home institution and contact details.

Model	Institution	Contact Person/Web address
GEPIC	EAWAG (Switzerland)	Christian Folberth/Hong Yang christian.folberth@eawag.ch hong.yang@eawag.ch
GAEZ-IMAGE	Netherland Environmental Assessment Agency, PBL (Netherland)	Elke Stehfest/Kathleen Neumann elke.stehfest@pbl.nl kathleen.neumann@pbl.nl
LPJ-GUESS	Lund University (Sweden), IMK-IFU, Karlsruhe Institute of Technology (Germany)	Stefan Olin/Thomas Pugh stefan.olin@nateko.lu.se thomas.pugh@imk.fzk.de
LPJmL	PIK (Germany)	Christoph Muller christoph.mueller@pik-potsdam.de
pDSSAT	University of Chicago (USA)	Joshua Elliott, jelliott@ci.uchicago.edu
PEGASUS	Tyndall Centre, University of East Anglia (UK)	Delphine Deryng d.deryng@uea.ac.uk

S2. Data

S2.1 GGCMs' simulated crop yields

We utilize the annual gridded rainfed crop yields from the six GGCMs of ISI-MIP Fastrack (Hempel *et al* 2013, Rosenzweig *et al* 2014) listed in table S1, over the GGCMs' historical simulation period spanning 1981-2004 (24 years)[18]. The number of grid-cells, counties and observations used in each crop~GGCM combination regression are summarized in table S3.

S2.2 USDA historical observed data

For comparison of the GGCMs' annual yields with the factual yields, we employed historical observed annual county level production ($bushel, bu$) and harvested areas ($acre, a$), made available by the U.S. Department of Agriculture (USDA)–National Agricultural Statistics Service (NASS): Quickstats 2.0 database[19]. The total (irrigated + rainfed) production and harvested area data utilized in this study covers ~90-1200 counties in the U.S. over the period 1981–2004 (24 years). Crop yields (bu/a) for each county are calculated as the ratio of production to harvested area. The conversion from bu/a to tons/hectare (t/ha) for each crop (for consistency with GGCMs' yield units in t/ha) is described as below in table S2.

Table S2. Conversion from bu/a to t/ha

Crop	bu/a	t/ha
Maize	1	0.0628
Wheat	1	0.0673
Soybeans	1	0.0673

To ensure comparability with the rainfed GGCMs' crop yields, we need to formulate a methodology to differentiate between the irrigated and rainfed crop production by county for the USDA crop yields. We utilized crop harvested area data from the 2012 USDA census of agriculture[20], and define rainfed counties for each of the three crops meeting the below criteria.

County (for crop type) is deemed as 'rainfed' county if

the share of crop harvested area is > 10 %, AND < 10 % of that harvested area is irrigated.

[18] Each GGCM panel is unbalanced. However, the time period (1981-2004) is consistent with USDA panel.

[19] http://quickstats.nass.usda.gov/ (accessed on 13 February 2017)

[20] https://www.agcensus.usda.gov/Publications/2012/Online_Resources/Ag_Census_Web_Maps/Data_download/index.php (accessed on 13 February 2017)

The final counties retained in regression analyses for each crop are shown in fig, S1 (USDA panel). The result is an unbalanced panel spanning years 1981-2004 (see details of observations and number of counties in table S3 under USDA).

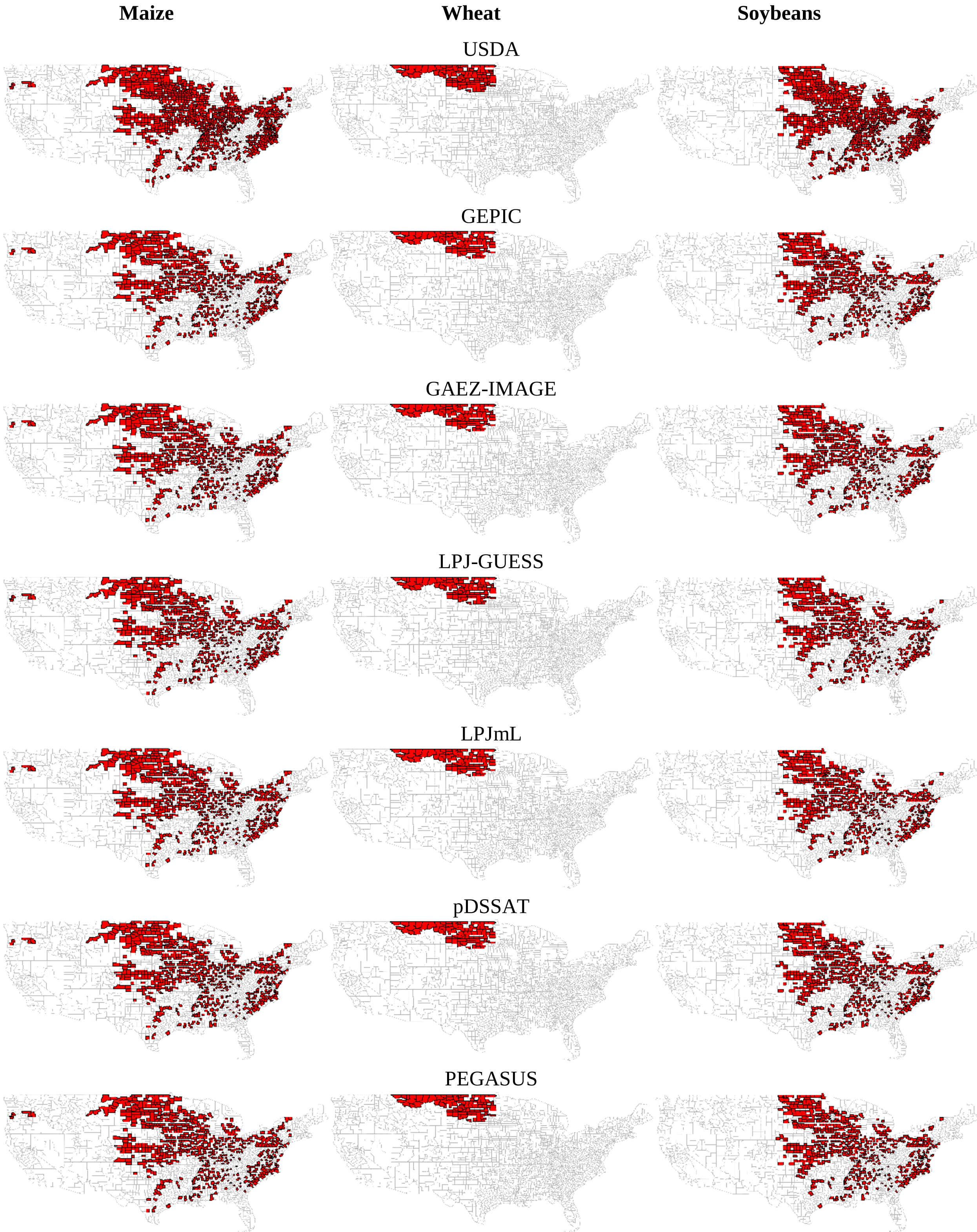

Fig. S1. Maps of USDA and GGCMs' rainfed counties used in this study for (i) maize (ii) wheat and (iii) soybeans.

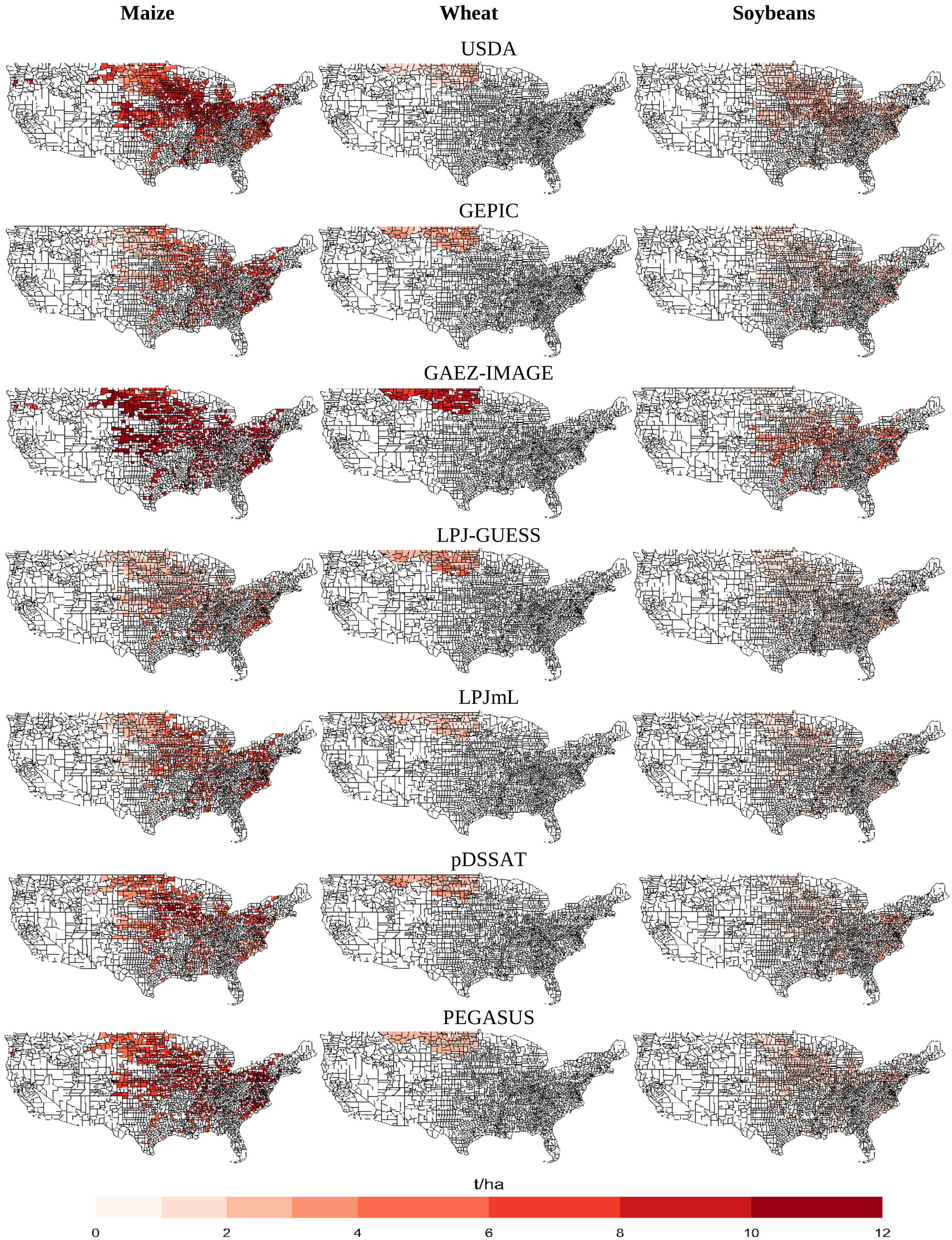

Fig. S2. Maps of USDA and GGCMs' historical (1981~2004) mean rainfed county yields (t/ha) for (i) maize (ii) wheat and (iii) soybeans.

Table S3. Number of observations, counties (in braces) and total grid-cells (in square braces) used in GGCMs and USDA regressions. The grid-cells and counties were retained for analyses if they reported yields in at least 10 of the total 24 years.

GGCM	Maize	Soybeans	Wheat
GEPIC	21,453 (728) [910]	18,123 (667) [777]	4,645 (88) [196]
GAEZ-IMAGE	21,939 (733) [919]	14,789 (670) [777]	4,800 (88) [200]
LPJ-GUESS	21,924 (730) [914]	18,672 (669) [778]	4,800 (88) [200]
LPJmL	21,851 (733) [919]	18,702 (786) [673]	4,800 (88) [200]
pDSSAT	20,926 (725) [912]	17,677 (771) [663]	4,773 (88) [200]
PEGASUS	21,819 (726) [910]	17,724 (772) [664]	4,799 (88) [200]
Multi-GGCM	129,912 (733) [919]	105,687 (786) [673]	28,617 (88) [200]
USDA, rainfed panel	27,370 (1,187)	24,606 (1,103)	1,855 (102)

S2.3 Crop growing seasons

In ISIMIP-FT simulations, the crops growing season (CGS) varies marginally not only for each crop-GGCM combination historical simulation, but also in the historical and future periods of GGCMs' simulated data (e.g. LPJ-GUESS and LPJmL mimic planting dates according to climatic conditions, see Rosenzweig *et al* 2014 SI for further details). To keep our analyses tractable, we subsume this heterogeneity and adopt the key simplification of a common fixed, four-month CGS as May-August ($MJJA$) for both USDA and GGCMs' crop panels; except for crop wheat for which April-August ($AMJJA$) was adopted.

Our definition of CGS by and large encapsulates the broader CGS across the GGCMs and crops. Moreover, by adopting a common CGS, we avoid the potential endogeneity problem with crop modellers' definition of when planting and harvesting begin in each year. Nevertheless, it is important to highlight that the definition of CGS may not likely be consistent with the actual CGS for the USDA data (e.g. 'spring + durum' wheat in some individual years of analyses could be partly grown outside the CGS ($AMJJA$) in our study area). The overall results of wheat could therefore be marginally influenced by this assumption (for e.g., see Lobell and Field 2007, Schauberger *et al* 2017)where in the results are fairly insensitive to the choice of CGS months for multiple crops examined in their study)

S3. Historical weather exposure for empirical analyses.

S3.1 GGCMs

All GGCM historical (1981-2004) crop yield simulation runs are forced with bias-corrected climate inputs (Hempel *et al* 2013) from HadGEM2-ES (Jones *et al* 2011). Here we matched the bias-corrected HadGEM2-ES frequency of days (bins) in the CGS, for daily mean temperature ($°C$) and total precipitation (mm) to GGCMs' generated realizations of yield in each year of the historical period. For consistency, we used the identical CGS truncations across the different GGCMs (i.e. $MJJA$ for crops maize and soybeans, and $AMJJA$ for wheat).

S3.2 USDA

Historical weather exposures (bins of daily mean temperature and total precipitation) for our empirical model are calculated from the 2.5 arcmin scale (~4 km) gridded Parameter-elevation Regressions on Independent Slopes Model (PRISM)[21] forcing files, spatially interpolated to county boundaries[22]. The PRISM model has been well documented in Daly *et al* (2008), has been widely used in earlier studies focusing on U.S. (such as Schlenker and Roberts 2006b, 2009, Roberts *et al* 2013, Auffhammer *et al* 2013), and more recently in Heft-Neal et al (2017). It is developed using climate observations from a wide range of monitoring networks, accounts for climate and elevation, and has highlighted by Schlenker

[21] PRISM daily mean temperature and total precipitation (1981~2004) were downloaded from http://www.ocs.orst.edu/prism/ (accessed on 13 February 2017)

[22] https://www.census.gov/geo/maps-data/data/cbf/cbf_counties.html (accessed on 13 February 2017)

and Roberts 2006a, is widely regarded as one of the best geographic interpolation procedures.

S4. Binning structure of temperature and precipitation in regressions

For our base specifications (eq. 1 in main text), our meteorological covariates are defined as the cumulative exposure to intervals ("bins") of T and P during the annual CGS in both USDA and GGCMs' regression specifications.

The bins $\{T_1, \ldots, T_J, P_1, \ldots, P_K\}$ are counts of number of days in the CGS at each GGCM grid-cell (county for USDA regression) spent in j intervals[23] of $T(Degree\ Celcius, °C)$ and k intervals of $P(millimiter\ per\ day, mm/d)$, where:

$j = \{< 7.5, 7.5\sim10, 10\sim12.5, 12.5\sim15, 15\sim17.5, 17.5\sim20, 20\sim22.5, 22.5\sim25, 25\sim27.5, 27.5\sim30, > 30\}$

and

$k = \{< 5, 5\sim10, 10\sim15, > 15\}$

The bins $j = 22.5\sim25\ °C$ and $k = 10\sim15\ mm/d$ were omitted in regressions as reference category. Thus with reference to eq. (1) in main text, each coefficient of T (P) indicates the impact on $log\ yield$ of an additional day in the j^{th} (k^{th}) interval, relative to a day in the dropped T (P) bin. All our regression specifications were run in R package Linear Fixed Effects (LFE) (Gaure 2013), which can handle arbitrary number of factors (fixed effects) and is tailored for fixed effect estimation on large panel data. To account for heteroscedasticity and autocorrelation in the error term $\varepsilon_{i,t,m}$ (eq. 1 in main text), we use robust standard errors (S.E.)[24] clustered by grid-cells.

[23] For each T and P bin except the extreme lower and upper values, the lower range is included in the count. The extreme bins are open-ended.

[24] The S.E.s calculated by R LFE are adjusted for the reduced degrees of freedom (DOF) coming from the dummies which are implicitly present. They are also small-sample corrected.

Table S4: Regression summary with Clustered Robust S.E. (in parenthesis, S.E. clustered by cross-sectional unit; in square braces clustered by cross-sectional unit and time): (i) maize, (ii) soybeans, (iii) wheat. Because two S.E.s are provided for each estimate, the stars denoting significance level are marked on the S.E. instead of on the estimates

	(i) Dependent variable: log yield (Maize)							
	USDA	GEPIC	GAEZ-IMAGE	LPJ-GUESS	LPJmL	pDSSAT	PEGASUS	Multi-GGCM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\overline{T} < 7.5^\circ$C	−0.006	0.076	0.005	0.003	0.024	0.007	−0.0124	0.017
	(0.001)***	(0.003)***	(0.001)***	(0.001)**	(0.002)***	(0.002)***	(0.002)***	(0.001)***
	[0.005]	[0.025]***	[0.004]	[0.006]	[0.018]	[0.007]	[0.007]*	[0.008]**
(7.5-10°C)	−0.006	0.030	−0.005	0.001	0.011	0.004	−0.025	0.002
	(0.001)***	(0.003)***	(0.001)***	(0.001)	(0.002)***	(0.001)***	(0.002)***	(0.001)**
	[0.004]	[0.022]	[0.003]	[0.005]	[0.007]	[0.007]	[0.006]***	[0.006]
(10-12.5°C)	−0.007	0.031	0.000	0.006	0.009	0.002	−0.020	0.005
	(0.001)***	(0.003)***	(0.001)	(0.001)***	(0.002)***	(0.001)**	(0.001)***	(0.001)***
	[0.003]**	[0.011]***	[0.002]	[0.002]***	[0.007]	[0.004]	[0.005]***	[0.003]
(12.5-15°C)	−0.006	0.023	−0.002	0.004	0.004	0.001	−0.016	0.002
	(0.001)***	(0.002)***	(0.001)***	(0.001)***	(0.001)***	(0.001)	(0.001)***	(0.001)***
	[0.002]***	[0.008]***	[0.001]	[0.002]*	[0.005]	[0.003]	[0.004]***	[0.002]
(15-17.5°C)	−0.002	0.025	−0.002	0.005	0.014	−0.001	−0.008	0.0069
	(0.000)***	(0.002)***	(0.000)***	(0.001)***	(0.001)***	(0.001)	(0.001)***	(0.001)***
	[0.002]	[0.009]***	[0.002]	[0.002]***	[0.003]***	[0.003]	[0.004]**	[0.003]**
(17-20°C)	−0.001	0.027	0.000	0.006	0.014	0.005	−0.003	0.008
	(0.000)***	(0.001)***	(0.000)	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
	[0.001]	[0.008]***	[0.001]	[0.001]***	[0.005]***	[0.003]**	[0.003]	[0.002]***
(20-22.5°C)	0.002	0.019	0.000	0.005	0.008	0.005	0.002	0.007
	(0.000)***	(0.001)***	(0.000)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
	[0.001]**	[0.005]***	[0.001]	[0.001]***	[0.002]***	[0.001]***	[0.002]	[0.001]***
(25-27.5°C)	−0.006	−0.021	0.000	−0.007	−0.009	−0.009	−0.009	−0.009
	(0.000)***	(0.001)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***	(0.001)***	(0.000)***
	[0.001]***	[0.004]***	[0.001]	[0.001]***	[0.003]***	[0.001]***	[0.002]***	[0.001]***
(27.5-30°C)	−0.016	−0.025	0.000	−0.009	−0.016	−0.010	−0.010	−0.012
	(0.000)***	(0.002)***	(0.000)	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
	[0.002]***	[0.007]***	[0.001]	[0.002]***	[0.003]***	[0.003]***	[0.003]***	[0.002]***
$\overline{T} > 30^\circ$C	−0.018	−0.030	0.001	−0.013	−0.020	−0.017	−0.022	−0.017
	(0.001)***	(0.002)***	(0.000)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.000)***
	[0.003]***	[0.009]***	[0.001]	[0.002]***	[0.006]***	[0.003]***	[0.004]***	[0.004]***
$\overline{P} < 5$ mm/day	−0.006	−0.020	0.000	−0.005	−0.015	−0.012	−0.002	−0.009
	(0.001)***	(0.002)***	(0.000)	(0.001)***	(0.001)***	(0.001)***	(0.001)	(0.001)***
	[0.003]**	[0.007]***	[0.001]	[0.002]***	[0.004]***	[0.003]***	[0.003]	[0.002]***
(5-10 mm/day)	−0.001	−0.010	0.000	−0.003	−0.007	−0.005	0.000	−0.004
	(0.001)	(0.003)***	(0.000)	(0.001)***	(0.002)***	(0.001)***	(0.002)	(0.001)***
	[0.001]	[0.006]*	[0.001]	[0.001]***	[0.003]**	[0.002]**	[0.003]	[0.002]**
$\overline{P} > 15$ mm/day	−0.001	0.020	0.001	0.010	0.017	0.008	−0.005	0.009
	(0.001)	(0.003)***	(0.001)***	(0.001)***	(0.002)***	(0.001)***	(0.002)***	(0.001)***
	[0.002]	[0.010]**	[0.002]	[0.003]***	[0.007]**	[0.004]*	[0.004]	[0.004]**
State time trends	Yes	No	No	No	No	No	No	No
Time dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	County FE	Grid-cell FE	Grid-cell FE	Grid-cell FE	Grid-cell FE	Grid-cell FE	Grid-cell FE	Grid-cell FE
Observations	27,370	21,453	21,939	21,924	21,851	20,926	21,819	129,912
Adjusted R^2	0.682	0.766	0.373	0.846	0.770	0.689	0.554	0.675
Residual SE	0.21 (df = 26134)	0.75 (df = 20507)	0.13 (df = 20984)	0.22 (df = 20974)	0.48 (df = 20896)	0.36 (df = 19979)	0.38 (df = 20873)	0.56 (df = 124393)

	(ii) Dependent variable: log yield (Soybeans)							
	USDA	GEPIC	GAEZ-IMAGE	LPJ-GUESS	LPJmL	pDSSAT	PEGASUS	Multi-GGCM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\overline{T} < 7.5°$C	−0.004	0.031	0.004	0.018	0.047	0.008	−0.060	0.008
	(0.001)***	(0.001)***	(0.003)	(0.001)***	(0.003)***	(0.005)	(0.003)***	(0.001)***
	[0.007]	[0.006]***	[0.012]	[0.008]**	[0.013]***	[0.024]	[0.025]**	[0.008]
(7.5-10°C)	−0.003	0.012	−0.011	0.011	0.007	0.011	−0.024	0.002
	(0.001)***	(0.001)***	(0.002)***	(0.001)***	(0.002)***	(0.004)***	(0.003)***	(0.001)**
	[0.004]	[0.006]**	[0.009]	[0.007]	[0.012]	[0.016]	[0.011]**	[0.006]
(10-12.5°C)	−0.008	0.015	−0.006	0.020	0.008	−0.003	−0.022	0.004
	(0.001)***	(0.001)***	(0.002)***	(0.001)***	(0.002)***	(0.003)	(0.002)***	(0.001)***
	[0.003]**	[0.004]***	[0.008]	[0.004]***	[0.008]	[0.010]	[0.008]***	[0.003]
(12.5-15°C)	−0.007	0.006	−0.004	0.017	0.006	−0.015	−0.024	−0.001
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.002)***	(0.001)***	(0.001)**
	[0.002]***	[0.003]**	[0.006]	[0.003]***	[0.005]	[0.010]	[0.007]***	[0.003]
(15-17.5°C)	−0.003	0.008	−0.003	0.015	0.017	−0.014	−0.009	0.005
	(0.000)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.002)***	(0.001)***	(0.001)***
	[0.002]	[0.003]***	[0.003]	[0.003]***	[0.006]***	[0.010]	[0.005]*	[0.002]*
(17-20°C)	−0.001	0.009	−0.002	0.012	0.018	−0.003	−0.002	0.007
	(0.000)***	(0.000)***	(0.007)**	(0.001)***	(0.001)***	(0.002)	(0.001)***	(0.001)***
	[0.002]	[0.003]***	[0.003]	[0.002]***	[0.006]***	[0.008]	[0.003]	[0.002]***
(20-22.5°C)	0.001	0.006	−0.002	0.008	0.014	0.006	−0.001	0.006
	(0.000)	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)*	(0.001)***
	[0.001]	[0.002]***	[0.002]	[0.001]***	[0.003]***	[0.006]	[0.002]	[0.002]***
(25-27.5°C)	−0.003	−0.011	−0.001	−0.010	−0.008	−0.023	−0.007	−0.010
	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.000)***
	[0.001]***	[0.001]***	[0.001]	[0.002]***	[0.003]**	[0.004]***	[0.002]***	[0.001]***
(27.5-30°C)	−0.010	−0.016	0.002	−0.013	−0.018	−0.0223	−0.008	−0.012
	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.000)***
	[0.002]***	[0.003]***	[0.002]	[0.002]***	[0.004]***	[0.005]***	[0.003]***	[0.002]***
$\overline{T} > 30°$C	−0.019	−0.017	0.001	−0.021	−0.015	−0.045	−0.020	−0.017
	(0.001)***	(0.000)***	(0.001)***	(0.001)***	(0.001)***	(0.002)***	(0.001)***	(0.000)***
	[0.003]***	[0.003]***	[0.003]	[0.004]***	[0.009]*	[0.015]***	[0.003]***	[0.003]***
$\overline{P} < 5$ mm/day	−0.006	−0.006	−0.002	−0.006	−0.004	−0.060	0.008	−0.011
	(0.001)***	(0.001)***	(0.001)*	(0.001)***	(0.002)**	(0.003)***	(0.002)***	(0.001)***
	[0.002]***	[0.002]**	[0.003]	[0.003]*	[0.004]	[0.008]***	[0.004]*	[0.003]***
(5-10 mm/day)	−0.001	−0.003	0.000	−0.002	−0.005	−0.015	0.009	−0.003
	(0.001)	(0.001)***	(0.001)	(0.001)*	(0.002)***	(0.003)***	(0.001)***	(0.001)***
	[0.001]	[0.001]*	[0.003]	[0.002]	[0.003]	[0.008]*	[0.003]***	[0.002]
$\overline{P} > 15$ mm/day	0.000	0.005	0.000	0.016	0.014	0.014	0.003	0.009
	(0.001)	(0.001)***	(0.001)	(0.001)***	(0.002)***	(0.003)***	(0.002)	(0.001)***
	[0.002]	[0.003]*	[0.003]	[0.005]***	[0.008]*	[0.009]	[0.005]	[0.003]***
State time trends	Yes	No	No	No	No	No	No	No
Time dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	County FE	Grid-cell FE	Grid-cell FE	Grid-cell FE	Grid-cell FE	Grid-cell FE	Grid-cell FE	Grid-cell FE
Observations	24,606	18,123	14,789	18,672	18,702	17,677	17,724	105,687
Adjusted R^2	0.653	0.851	0.325	0.845	0.654	0.672	0.478	0.586
Residual Std. Error	0.19 (df = 23459)	0.21 (df = 17310)	0.28 (df = 14083)	0.26 (df = 17858)	0.51 (df = 17880)	0.80 (df = 16870)	0.41 (df = 16916)	0.59 (df = 101097)

	(iii) Dependent variable: log yield (Wheat)							
	USDA	GEPIC	GAEZ-IMAGE	LPJ-GUESS	LPJmL	pDSSAT	PEGASUS	Multi-GGCM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\overline{T} < 7.5°$C	0.003	0.003	−0.001	0.014	0.041	0.003	−0.014	0.008
	(0.002)**	(0.002)	(0.001)***	(0.001)***	(0.005)***	(0.003)	(0.002)***	(0.002)***
	[0.006]	[0.011]	[0.002]	[0.005]***	[0.017]**	[0.006]	[0.013]	[0.005]
(7.5-10°C)	0.004	0.025	−0.002	0.014	0.040	0.018	−0.008	0.014
	(0.003)	(0.002)***	(0.000)***	(0.001)***	(0.004)***	(0.002)***	(0.002)***	(0.001)***
	[0.007]	[0.009]***	[0.002]	[0.004]***	[0.012]***	[0.004]***	[0.010]	[0.004]***
(10-12.5°C)	−0.006	0.026	0.000	0.015	0.026	0.009	0.004	0.013
	(0.002)***	(0.001)***	(0.001)	(0.001)***	(0.002)***	(0.002)***	(0.001)***	(0.001)***
	[0.006]	[0.007]***	[0.001]	[0.003]***	[0.008]***	[0.005]**	[0.006]	[0.003]***
(12.5-15°C)	0.003	0.019	0.000	0.013	0.011	0.005	0.001	0.008
	(0.002)	(0.001)***	(0.000)	(0.001)***	(0.002)***	(0.001)***	(0.002)	(0.001)***
	[0.004]	[0.005]***	[0.001]	[0.002]***	[0.009]	[0.004]	[0.004]	[0.002]***
(15-17.5°C)	−0.003	0.019	0.000	0.013	0.012	0.007	0.005	0.009
	(0.002)*	(0.001)***	(0.000)	(0.001)***	(0.002)***	(0.001)***	(0.002)***	(0.001)***
	[0.004]	[0.004]***	[0.001]	[0.002]***	[0.006]*	[0.004]**	[0.006]	[0.002]***
(17-20°C)	−0.006	0.011	−0.001	0.006	0.000	0.000	0.003	0.003
	(0.002)***	(0.001)***	(0.000)*	(0.001)***	(0.002)	(0.001)	(0.002)*	(0.001)***
	[0.004]	[0.004]***	[0.001]	[0.002]***	[0.008]	[0.003]	[0.006]	[0.002]
(20-22.5°C)	−0.009	0.003	−0.001	−0.001	−0.009	−0.004	0.000	−0.002
	(0.002)***	(0.001)***	(0.000)***	(0.001)	(0.002)***	(0.001)***	(0.001)	(0.001)***
	[0.004]**	[0.003]	[0.001]	[0.002]	[0.005]*	[0.004]	[0.004]	[0.002]
(25-27.5°C)	−0.026	0.004	−0.001	−0.002	−0.011	0.002	−0.004	−0.002
	(0.003)***	(0.002)**	(0.000)**	(0.001)*	(0.002)***	(0.002)	(0.002)**	(0.001)**
	[0.009]***	[0.006]	[0.001]	[0.002]	[0.006]*	[0.005]	[0.006]	[0.002]
(27.5-30°C)	−0.037	−0.022	0.001	−0.009	−0.011	−0.016	−0.040	−0.016
	(0.005)***	(0.003)***	(0.000)***	(0.001)***	(0.003)***	(0.003)***	(0.002)***	(0.001)***
	[0.013]***	[0.009]**	[0.001]	[0.004]**	[0.008]	[0.008]*	[0.012]***	[0.003]***
$\overline{T} > 30°$C	−0.075	−0.004	−0.002	−0.003	−0.059	−0.017	−0.028	−0.019
	(0.017)***	(0.006)	(0.001)**	(0.003)	(0.011)***	(0.007)**	(0.007)***	(0.003)***
	[0.026]***	[0.009]	[0.002]	[0.008]	[0.014]***	[0.006]***	***	[0.004]***
$\overline{P} < 5$ mm/day	−0.016	−0.017	0.001	−0.019	−0.011	−0.006	−0.006	−0.010
	(0.003)***	(0.002)***	(0.001)*	(0.001)***	(0.004)***	(0.002)***	(0.002)***	(0.001)***
	[0.007]**	[0.006]***	[0.001]	[0.004]***	[0.012]	[0.005]	[0.007]	[0.003]***
(5-10 mm/day)	−0.010	−0.005	0.001	−0.008	0.008	0.007	−0.007	−0.001
	(0.004)**	(0.002)**	(0.001)**	(0.001)***	(0.004)**	(0.002)***	(0.002)***	(0.001)
	[0.006]*	[0.003]*	[0.001]	[0.002]***	[0.009]	[0.004]*	[0.005]	[0.002]
$\overline{P} > 15$ mm/day	−0.015	0.010	0.001	0.010	−0.016	0.001	0.000	0.001
	(0.005)***	(0.003)***	(0.001)*	(0.001)***	(0.004)***	(0.002)	(0.002)	(0.001)
	[0.007]*	[0.010]	[0.001]	[0.004]***	[0.008]**	[0.004]	[0.010]	[0.004]
State time trends	Yes	No	No	No	No	No	No	No
Time dummies	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	County FE	Grid-cell FE	Grid-cell FE	Grid-cell FE	Grid-cell FE	Grid-cell FE	Grid-cell FE	Grid-cell FE
Observations	1,855	4,645	4,800	4,800	4,800	4,773	4,799	28,617
Adjusted R^2	0.431	0.752	0.3706	0.829	0.620	0.580	0.695	0.734
Residual Std. Error	0.28 (df = 1736)	0.24 (df = 4413)	0.07 (df = 4564)	0.13 (df = 4564)	0.34 (df = 4564)	0.22 (df = 4537)	0.23 (df = 4563)	0.32 (df = 27385)

S5. Variation in historical observed (USDA) and simulated (GGCMs) yields empirically attributed to weather (T and P bins)

The adjusted R^2 (in table S4) derived from our regression specifications track how much of the cross-section/time-series variation in yields is explained by not only the predictors[25] (T and P), but also by the grid-cell fixed effects (μ_i) and the time effects ($f(t) = \tau_t$), or the county fixed effects (μ_i) and the state specific time trend ($f(t) = \lambda_s t$).

To gauge how much on average the weather variables (T and P) explain the cross-section/time-series variation in yields, table S5 summarizes the adjusted R^2 by stripping out the influencing effects of the idiosyncratic unobserved shocks (μ_i and $f(t)$) in eq. 1. These are obtained directly from R LFE package 'Projected Model $adj - R^2$'

Table S5. Percentage of variation explained by the covariates (T and P), for base specification with time effects, and with state specific time trend in lieu of time effects (in braces)

GGCM	Maize	Wheat	Soybeans
GEPIC	30% (61%)	29% (51%)	53% (74%)
GAEZ-IMAGE	2% (4%)	0% (1%)	0% (11%)
LPJ-GUESS	39% (58%)	43% (63%)	53% (74%)
LPJmL	31% (49%)	15% (24%)	22% (43%)
pDSSAT	27% (48%)	9% (21%)	32% (50%)
PEGASUS	20% (35%)	22% (49%)	17% (32%)
Multi-Model	10% (19%)	4% (7%)	10% (22%)
USDA	16% (46%)	13% (30%)	15% (32%)

Focusing on GGCMs (table S5), GAEZ-IMAGE is not well captured by the regression specifications (eq. 1 in main text). This could be partly attributed to the low inter-annual variation in crop yields as GAEZ-IMAGE simulates yields at 5-yearly time step in contrast to the yield simulated annually by other GGCMs[26]. It then interpolates the crop yields for the missing years. This results in lower inter-annual

[25] There are total 13 weather response parameters (10 temperature bins and 3 precipitation bins) in our regressions model (eqs.1 of main text). See table S4 for details on number of fixed effects, time effects and state specific time trends.

[26] https://www.isimip.org/outputdata/caveats-fast-track/

variation of yields vis-à-vis other GGCMs, thereby resulting in low residual variation for the weather variables to capture.

Compared to the $adj - R^2$ for maize and soybean, the $adj - R^2$ for wheat is generally low across all GGCMs, except for LPJ-GUESS and PEGASUS. GGCMs in ISIMIP-FT decide internally on the type of wheat to simulate. Preference to grow spring or winter wheat in GGCMs depend on temperature thresholds etc. (with some exceptions, e.g. LPJmL has preference for winter wheat, and PEGASUS simulates only spring wheat). Therefore, it is plausible that some variation in GGCMs' wheat yields can be attributed to weather exposure outside the choice of our growing season months $(AMJJA)$. Nevertheless, by and large our specification (eq. 1 in main text) explain between one-fifth to half of the variance in each of the three crops and six GGCMs, and slightly lower in the multi-model regression specification.

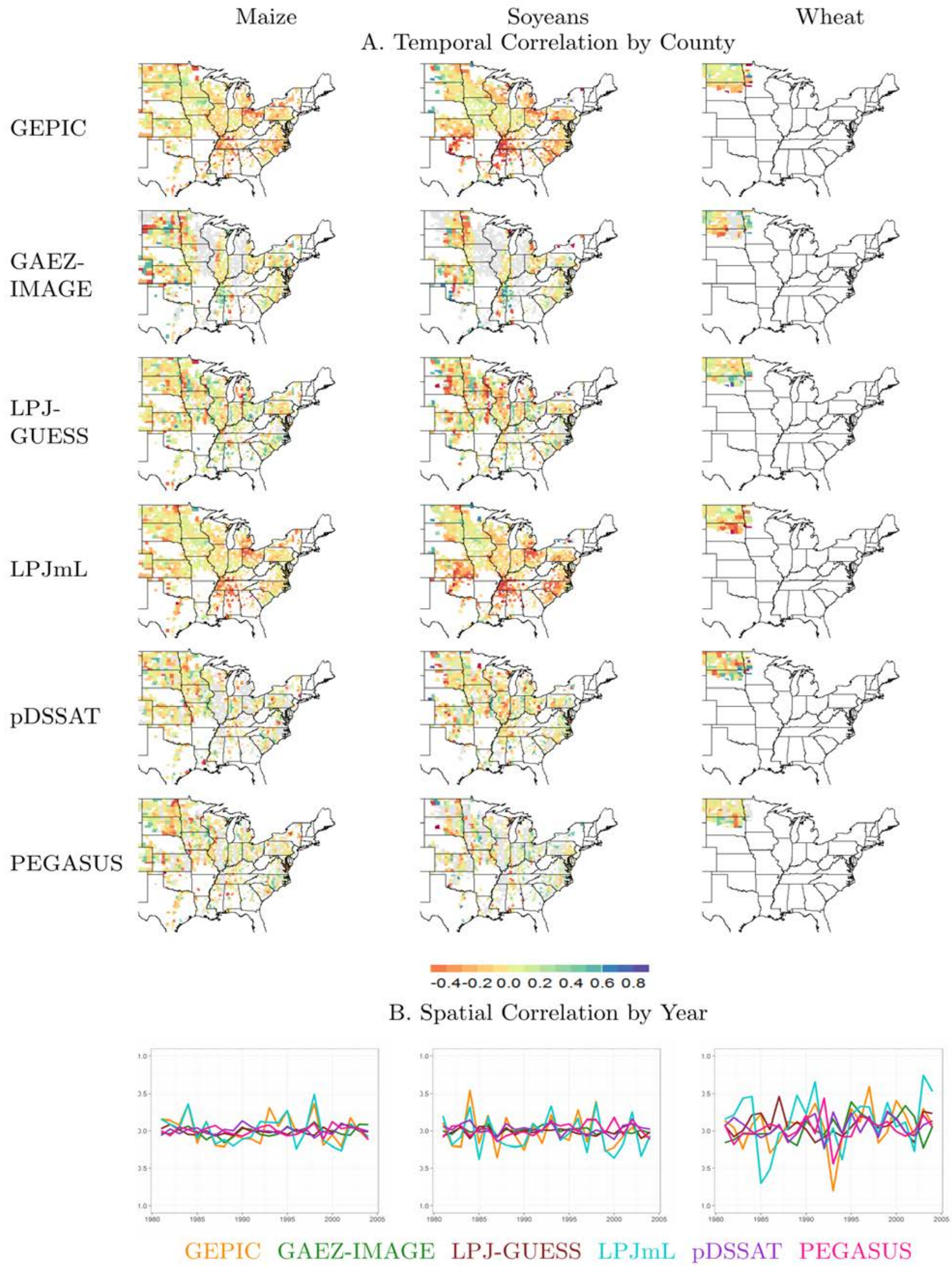

Fig. S3: Correlations between GGCM simulated and USDA recorded percentage anomalies in de-trended yields for maize, soybeans and wheat. Anomalies are calculated as the % deviation of each county's de-trended yield from its own 1981-2004 mean.

S6. Sensitivity checks using different regression specifications

To ensure that the estimate coefficient responses of GGCMs summarized in fig. 3 of main text did not depend on an overly specific choice of regression specification, and in line with common practice in statistical modelling (e.g. Urban *et al* 2015, Schlenker and Roberts 2009, Baylis *et al* 2011, Lobell *et al* 2011, Blanc 2016, Schauberger *et al* 2017), we consider two further suites of regression specifications.

S6.1 Mean responses of simulated yield using state time-trend specification for all GGCMs

Fig. S4 shows the mean responses of GGCMs' log $yields$ to temperature and precipitation exposure, using a specification with state specific time trend in lieu of time dummies. As highlighted in main text, GGCMs hold management practices and technology parameter constant to the year 2000 (although some GGCMs do include some endogenous form of adaptation (see table S6 for details), and therefore time effects are considered more appropriate for GGCMs. Nevertheless, for comparability with the empirical specification for USDA, we re-examine the GGCMs' estimated coefficient responses using state-specific time trends.

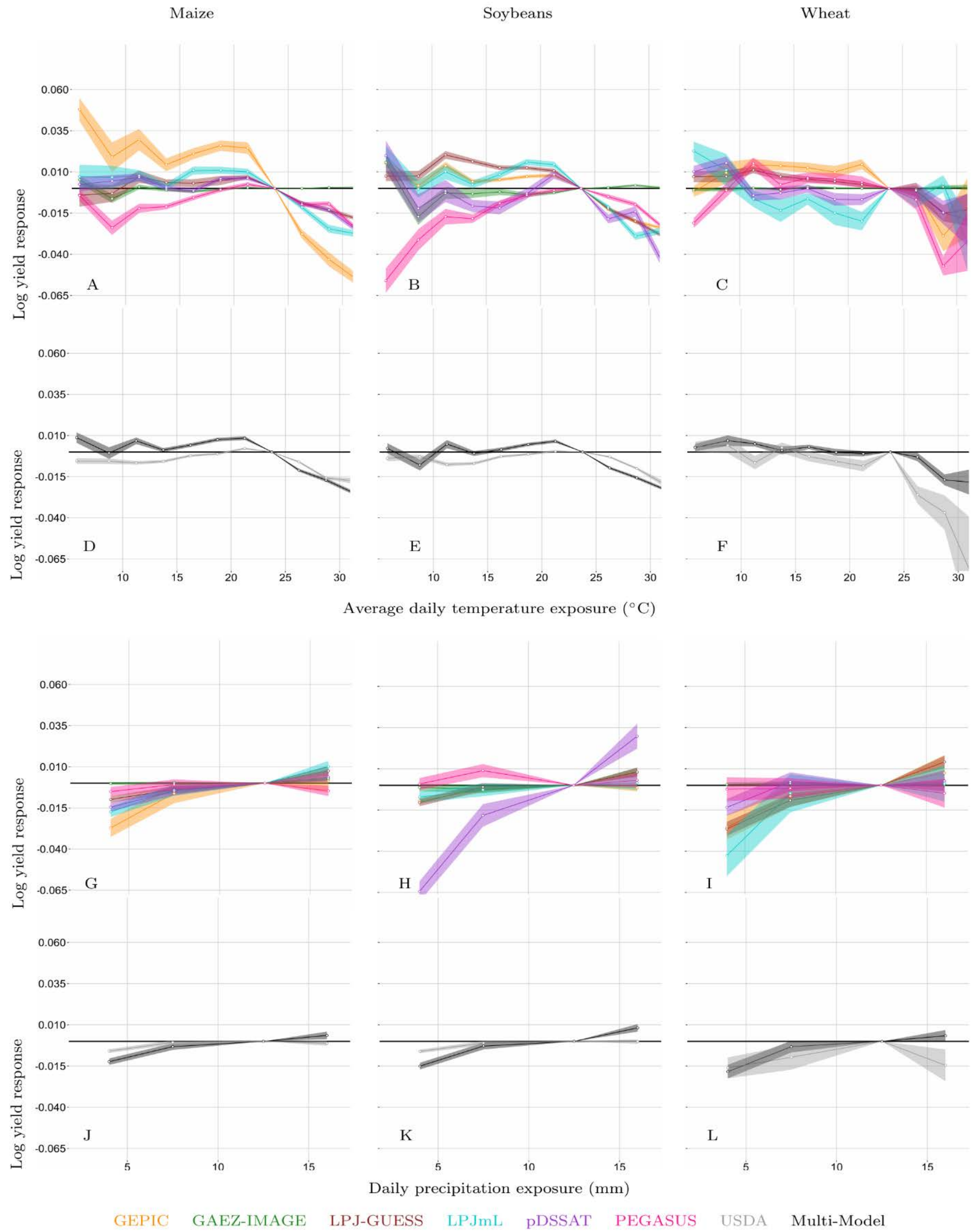

Fig. S4. Mean responses (solid lines) and confidence intervals (95%) (shaded areas) of log yield to temperature and precipitation exposure for maize, soybeans and wheat, with state time trends. Responses are normalized relative to the number of days with temperatures $22.5 - 25°C$ and precipitation $10 - 15\ mm/day$, represented by the heavy horizontal axis. Shaded confidence intervals are computed from robust standard errors clustered at the cross-sectional units. For USDA, the mean responses are from the same specification as in fig. 3 of main text.

As noted by other studies (e.g. Schlenker and Roberts 2009, Lobell *et al* 2011, Schauberger *et al* 2017); comparing figures 3 (main text) and S4, the responses of GGCMs' crop yields are robust to modification in econometric specifications.

S6.2 Mean responses of simulated yield using mean growing season temperature and precipitation

A similar pattern of nonlinear effects of temperature and precipitation remain if a commonly used parsimonious specification is utilized, instead of our semi-parametric binning approach. The use of mean growing season temperature (T), mean (or total) growing season precipitation (P) (eq. S1[27]), show that the generally heterogeneous responses of GGCMs' $log\ yield$ responses to the weather variables used in our study, generally disagree both in magnitude and response thresholds (figure S5) with the observed.

$$y_{i,t,m} = \mu_i + f(t) + \beta_1 T_{i,t,m} + \beta_2 T_{i,t,m}^2 + \beta_3 P_{i,t,m} + \beta_4 P_{i,t,m}^2 + \beta_5 T_{i,t,m} * P_{i,t,m} + \varepsilon_{i,t,m} \qquad \text{(S1)}$$

where T is the mean growing season (MJJA for maize and soybeans, AMJJA for wheat) temperature ($°C$), P is mean growing season precipitation (mm), and the remaining terms as per the nomenclature used in eq. 1 of main text. In lieu of mean growing season precipitation, total growing season precipitation was also examined (results are near similar and available upon request).

[27] For instance, see Lobell and Burke 2010, Lobell *et al* 2011, Blanc 2017 for a good discussion on the underlying reasons of choosing specifications with mean growing season variables and their quadratic terms, along with interactions between T and P.

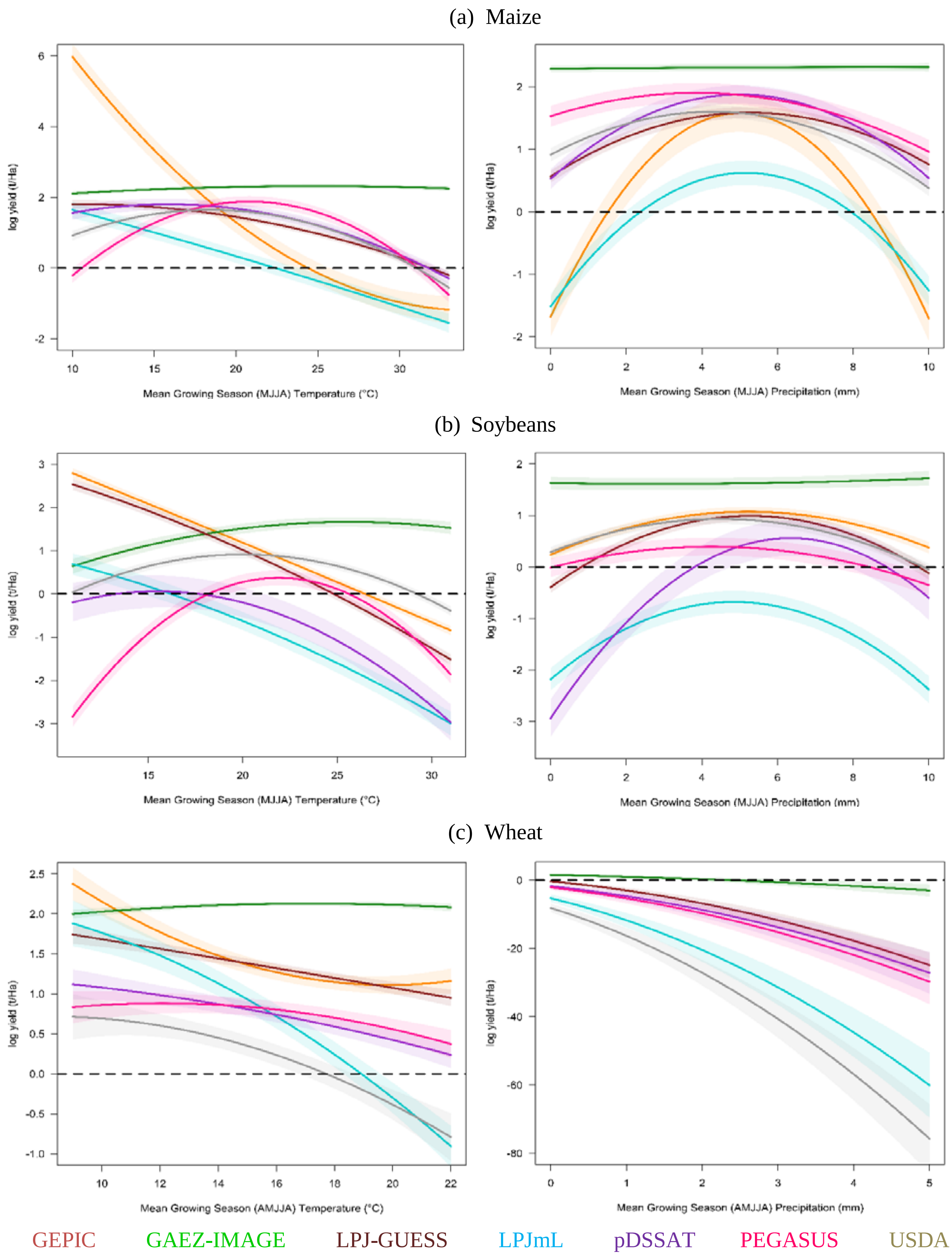

Fig. S5. Mean log $yields$ responses (solid lines) and confidence intervals (95%) (shaded areas) to mean growing season temperature ($°C$) and precipitation (mm) exposure for (a) maize, (b) soybeans and (c) wheat (eq. S1). Horizontal dashed line (at y=0) shown for reference. Shaded confidence intervals are computed from robust standard errors clustered at the cross-sectional units. Growing seasons are defined as in main text (May-August for maize and soybeans, and April-August for wheat)

S7. Meta-Analyses

Using the five sets of characteristics (illustrated in bold in table S6), we construct binary variables for explanatory variables in the meta-analysis regression (eq. 5 in main text).

Table S6: Heterogeneity in GGCMs used in this study, adapted from Rosenzweig *et al* (2014).

Parameters	**GEPIC**	**GAEZ-IMAGE**	**LPJ-GUESS**	**LPJmL**	**pDSSAT**	**PEGASUS**
Model Type	Site-based	Agro-ecological zone (AEZ)	Agro-ecosystem	Agro-ecosystem	Site-based	Agro-ecosystem
Crop Yield	Actual	Potential	Potential	Actual	Actual	Actual
Crop Cultivars	Yes	Yes	Yes	No	No[a]	Yes
Planting window	Dynamic[b] (climate adaptation)	Implicit Planting dates (climate adaptation)	Fixed[c]	Fixed planting date	Fixed (by taking the historical average, for all years in future)	Dynamic (climate adaptation)
Nitrogen (N)[d] fertilization	Yes	No	No	No	Yes	Yes
Type of stress[e]	W, T, **H**, O_2, N, P, BD, Al	W, T, BD	W, T	W, T	W, T, **H**, O_2, N	W, T, **H**, N, P, K
Light Utilization (Photosynthesis)	Radiation use efficiency (RUE)	RUE	Leaf	Leaf	RUE (Leaf for Soybeans)	RUE
Model Calibration and Type_*SpatialResolution*	Yes Site-specific_*National*	No	No	Yes Global_*National*	Yes Site-specific_*Field-scale*	Yes Global_*Gridcell*
Method used in Evapotranspiration (ET) calculation	Penman-Monteith	Priestly-Taylor	Priestly-Taylor	Priestly-Taylor	Priestly-Taylor	Priestly-Taylor

[a] For pDSSAT, cultivar choice, fertilizer application etc. are fixed by the historical average of all future years.

[b] Dynamic: Automatic adjustments of planting and harvesting dates due to annual weather conditions; an internal model process.

[c] Fixed: planting windows are determined using historical values based on literature. LPJ-GUESS allows planting dates adaptation within +/-15 days of calculated optimum values, but planting window is fixed.

[d] For GEPIC, fertilizer application rate is adjusted flexibly according to Nitrogen (N) stress. pDSSAT and PEGASUS hold fertilizer application rates constant.

[e] Water (W), Temperature (T), Heat (H), Oxygen (O_2), Phosphorous (P), Bulk Density (BD), Aluminum (Al), Potassium (K)

We regress the vector of differences in combined set of estimated semi-elasticities from GGCMs and USDA, $\Delta\zeta(\widehat{\boldsymbol{\beta}}^T, \widehat{\boldsymbol{\beta}}^P) = \zeta\left(\widehat{\boldsymbol{\beta}}^T, \widehat{\boldsymbol{\beta}}^P\right)^{GGCM} - \zeta\left(\widehat{\boldsymbol{\beta}}^T, \widehat{\boldsymbol{\beta}}^P\right)^{USDA}$, using the set of parameters describing models' dimensions as a vector of dummies (Specification 1)[28]. We also test i) two additional models in which only the vector of differences in temperature (Specification 2) and precipitation (Specification 3) semi-elasticities are used as dependent variables[29] and ii) three additional models in which model parameter dummies are interacted with the extreme high temperature (*hi_t*) and low precipitation (*lo_p*) bins, namely as $\{25\sim27.5, 27.5\sim30, >30\}$℃ and $\{<5, 5\sim10\}\, mm/day$ (Specifications 4, 5, and 6). Specifications (1) and (4) enable us to examine the influence of GGCMs key parameter dimensions averaged across all temperature and precipitation bins. Specifications (4), (5), and (6) enable us to attribute the key parameters that influence the divergence in GGCMs' responses to the extreme temperature or precipitation bins.

[28] The dependent variable is the difference in the estimated coefficient of the 13 temperature and precipitation bins from eq. 1 of main text, for each of the 6 GGCMs (thus totalling 72 observations using the parameters in bold from table S6).

[29] Specifications 2 and 3 have 60 and 18 observations for the six GGCMs for temperature and precipitation, respectively.

Table S7: Effects of model characteristics on GGCM-USDA divergence in (A) soybeans and (B) wheat $log\ yield$ responses. Robust standard errors (S.E.) are reported in parenthesis

A. Soybeans

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\zeta[\widehat{\beta}^P, \widehat{\beta}^T]$	$\Delta\zeta[\widehat{\beta}^T]$	$\Delta\zeta[\widehat{\beta}^P]$	$\Delta\zeta[\widehat{\beta}^P, \widehat{\beta}^T]$	$\Delta\zeta[\widehat{\beta}^T]$	$\Delta\zeta[\widehat{\beta}^P]$
Potential yield	-0.012*	-0.011*	0.002	-0.011**	-0.020***	0.003
	(0.006)	(0.006)	(0.003)	(0.005)	(0.006)	(0.007)
Endog. cultivar	0.022***	0.022***	0.001	0.029***	0.038***	0.005
	(0.007)	(0.007)	(0.002)	(0.006)	(0.007)	
Endog. sowing date	-0.007*	-0.008*		-0.018***	-0.018***	
	(0.004)	(0.005)		(0.003)	(0.003)	
Heat stress	-0.023***	-0.026***	0.008**	-0.025***	-0.037***	-0.002
	(0.008)	(0.008)	(0.003)	(0.009)	(0.009)	
Site calibration	-0.007	-0.004		0.004	-0.004	
	(0.005)	(0.004)		(0.004)	(0.004)	
$T > 30°$C						
× Potential yield				0.007	0.031***	
				(0.009)	(0.007)	
× Endog. cultivar				-0.028***	-0.053***	
				(0.009)	(0.008)	
× Endog. sowing date				0.033***	0.033***	
				(0.006)	(0.006)	
× Heat stress				0.008	0.035***	
				(0.010)	(0.009)	
× Site calibration				-0.023***		
				(0.005)		
$P < 5$mm						
× Potential yield				-0.020		-0.001
				(0.017)		(0.007)
× Endog. cultivar				0.002		-0.006***
				(0.017)		(0.001)
× Endog. sowing date				0.020***		
				(0.003)		
× Heat stress				0.004		0.014***
				(0.018)		(0.002)
× Site calibration				-0.037**		
				(0.016)		
Adj. F	4.289***	4.885***	1.553	42.577***	24.052***	2.325*
	(df = 4;77)	(df = 4;59)	(df = 2;17)	(df = 14;77)	(df = 8;59)	(df = 5;17)
Obs.	78	60	18	78	60	18
Adj R Sq.	0.128	0.190	-0.110	0.390	0.319	-0.339

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

B. Wheat

	(1) $\Delta\zeta[\widehat{\boldsymbol{\beta}}^P, \widehat{\boldsymbol{\beta}}^T]$	(2) $\Delta\zeta[\widehat{\boldsymbol{\beta}}^T]$	(3) $\Delta\zeta[\widehat{\boldsymbol{\beta}}^P]$	(4) $\Delta\zeta[\widehat{\boldsymbol{\beta}}^P, \widehat{\boldsymbol{\beta}}^T]$	(5) $\Delta\zeta[\widehat{\boldsymbol{\beta}}^T]$	(6) $\Delta\zeta[\widehat{\boldsymbol{\beta}}^P]$
Potential yield	0.010	0.007	0.002	-0.006	0.0003	-0.004
	(0.009)	(0.011)	(0.008)	(0.005)	(0.007)	(0.004)
Endog. cultivar	0.008	0.014	0.009	0.020***	0.012	0.024***
	(0.010)	(0.013)	(0.007)	(0.005)	(0.007)	(0.000)
Endog. sowing date	-0.003	-0.006		-0.011***	-0.011***	
	(0.008)	(0.010)		(0.003)	(0.003)	
Heat stress	0.003	-0.0005	0.00004	-0.007	-0.0005	-0.010***
	(0.008)	(0.010)	(0.007)	(0.006)	(0.008)	(0.000)
Site calibration	0.015***	0.016***		0.008***	0.016***	
	(0.004)	(0.005)		(0.002)	(0.006)	
$T > 30°$C						
$\times$ Potential yield				0.049**	0.023	
				(0.023)	(0.020)	
$\times$ Endog. cultivar				-0.022	0.006	
				(0.027)	(0.024)	
$\times$ Endog. sowing date				0.015	0.015	
				(0.019)	(0.019)	
$\times$ Heat stress				0.027	-0.00002	
				(0.023)	(0.020)	
$\times$ Site calibration				0.027**		
				(0.011)		
$P < 5$mm						
$\times$ Potential yield				0.032***		0.009
				(0.006)		(0.006)
$\times$ Endog. cultivar				-0.046***		-0.023***
				(0.007)		(0.002)
$\times$ Endog. sowing date				0.025***		
				(0.005)		
$\times$ Heat stress				0.025***		0.015***
				(0.007)		(0.004)
$\times$ Site calibration				0.005		
				(0.003)		
Adj. F	4.289***	4.885***	1.553	42.577***	24.052***	2.325*
	(df = 4;77)	(df = 4;59)	(df = 2;17)	(df = 14;77)	(df = 8;59)	(df = 5;17)
Obs.	78	60	18	78	60	18
Adj. R Sq.	0.350	0.342	0.283	0.564	0.530	0.401

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table S8. Two-sided Welch t-test for significant difference in regression coefficients (GGCM – USDA), based on robust standard errors clustered at the cross-sectional units. Test results in parenthesis are based on two-way clustered robust standard errors (Cameron *et al* 2011), clustered by the cross-sectional units and time.
H_0: Coefficients are not different

(a) **GEPIC**

T, P bins	**Maize (Coeff diff)**	**t**	**Soybeans (Coeff diff)**	**t**	**Wheat (Coeff diff)**	**T**
tas_7p5lo	0.081	25.430*** (3.117)***	0.035	23.979*** (3.841) ***	-0.001	-0.298 (-0.055)
tas_7p5_10	0.036	11.838*** (1.613)*	0.015	11.307*** (2.118) **	0.021	6.740*** (1.921) **
tas_10_12p5	0.037	14.664*** (3.120)***	0.023	22.413*** (4.107) ***	0.032	12.463*** (3.677) ***
tas_12p5_15	0.030	16.323*** (3.368)***	0.013	18.235*** (3.920) ***	0.017	8.209*** (2.501) ***
tas_15_17p5	0.028	18.182*** (2.943)***	0.011	17.989*** (3.425) ***	0.022	10.678*** (3.785) ***
tas_17p5_20	0.029	20.495*** (3.461)***	0.010	19.469*** (2.992) ***	0.017	8.582*** (2.818) ***
tas_20_22p5	0.016	11.850*** (3.285)***	0.006	10.478*** (2.600) ***	0.012	5.865*** (2.287) **
tas_25_27p5	-0.015	-11.570*** (-3.626)***	-0.008	-15.624*** (-4.884) ***	0.030	9.530*** (2.879) ***
tas_27p5_30	-0.009	-4.793*** (-1.229)	-0.006	-9.948*** (-1.721) *	0.015	2.496* (0.913)
tas_g30	-0.013	-7.272*** (-1.359)	0.003	2.858*** (0.598)	0.071	3.862*** (2.583) ***
p_5lo	-0.014	-5.821*** (-1.852)*	0.001	0.608 (0.173)	-0.001	-0.286 (-0.117)
p_5_10	-0.010	-3.632*** (-1.672)*	-0.002	-1.728* (-1.095)	0.004	0.973 (0.680)
p_15up	0.021	6.885*** (2.111)**	0.005	4.535*** (1.461)	0.024	4.360*** (1.968) **

(b) **GAEZ-IMAGE**

tas_7p5lo	0.010	8.082*** (1.573)	0.008	2.648*** (0.537)	-0.005	-2.786*** (-0.785)
tas_7p5_10	0.000	0.247 (0.054)	-0.008	-3.413*** (-0.817)	-0.006	-2.239* (-0.815)
tas_10_12p5	0.007	8.697*** (1.727)*	0.002	0.998 (0.191)	0.007	3.165*** (1.163)
tas_12p5_15	0.004	7.924*** (2.304)**	0.003	2.388** (0.461)	-0.003	-1.503* (-0.615)
tas_15_17p5	0.000	0.263 (0.055)	-0.005	-0.454 (-0..119)	0.003	1.671** (0.677)
tas_17p5_20	0.001	2.294** (0.534)	0.000	-0.058 (-0.011)	0.005	3.293*** (1.134)
tas_20_22p5	-0.002	-4.996*** (-1.512)	-0.003	-4.133*** (-1.176)	0.008	4.601*** (1.940) **
tas_25_27p5	0.006	17.519*** (4.697)***	0.002	3.868*** (1.299)	0.025	9.287*** (2.954) ***
tas_27p5_30	0.016	35.298*** (8.543)***	0.012	21.418*** (4.374) ***	0.038	7.085*** (2.846) ***
tas_g30	0.018	20.674*** (5.645)***	0.021	20.476*** (5.248) ***	0.073	4.205*** (2.846) ***
p_5lo	0.006	9.092*** (2.061)**	0.004	3.528*** (1.035)	0.017	5.195*** (2.292) **
p_5_10	0.001	1.289 (0.552)	0.001	0.614 (0.322)	0.011	2.806*** (1.907) *
p_15up	0.003	2.818*** (0.895)	0.000	0.032 (0.013)	0.016	3.218*** (2.106) **

$* p < 0.1; ** p < 0.05; *** p < 0.01$

(c) **LPJ-GUESS**

T, P bins	Maize (Coeff diff)	t	Soybeans (Coeff diff)	t	Wheat (Coeff diff)	t
tas_7p5lo	0.009	5.258*** (1.109)	0.022	12.752*** (2.116) **	0.011	5.037*** (1.463)
tas_7p5_10	0.007	4.997*** (1.005)	0.014	8.980*** (1.708) *	0.010	3.473*** (1.233)
tas_10_12p5	0.013	12.948*** (3.266)***	0.028	25.534*** (5.449) ***	0.021	9.453*** (3.297) ***
tas_12p5_15	0.010	10.204*** (3.766)***	0.024	27.641*** (7.043) ***	0.011	5.767*** (2.245) **
tas_15_17p5	0.007	9.749*** (2.938)***	0.018	24.705*** (5.820) ***	0.015	8.865*** (3.513) ***
tas_17p5_20	0.008	9.467*** (3.773)***	0.014	21.745*** (5.468) ***	0.012	6.996*** (2.421) **
tas_20_22p5	0.003	4.644*** (1.946)**	0.008	12.542*** (3.840) ***	0.008	4.337*** (1.809) *
tas_25_27p5	-0.001	-2.242** (-0.671)	-0.007	-11.706*** (-3.129) ***	0.024	8.499*** (2.761) ***
tas_27p5_30	0.006	9.137*** (2.674)***	-0.003	-3.795*** (-0.890)	0.028	5.028*** (1.972) **
tas_g30	0.004	4.408*** (1.129)	-0.002	-1.690*** (-0.317)	0.072	4.054*** (2.684) ***
p_5lo	0.001	0.566*** (0.161)	0.001	0.506 (0.149)	-0.003	-0.827 (-0.358)
p_5_10	-0.003	-2.372** (-1.613)*	-0.001	-0.800 (-0.495)	0.002	0.510 (0.342)
p_15up	0.011	9.233*** (3.058)***	0.016	12.330*** (2.961) ***	0.025	4.806*** (2.925) ***

(d) **LPJmL**

T, P bins	Maize (Coeff diff)	t	Soybeans (Coeff diff)	t	Wheat (Coeff diff)	t
tas_7p5lo	0.029	11.194*** (1.562)*	0.051	17.244*** (3.505) ***	0.038	6.950*** (2.142) **
tas_7p5_10	0.016	7.220*** (1.953)**	0.010	4.247*** (0.810)	0.036	8.351*** (2.662) ***
tas_10_12p5	0.015	9.835*** (2.027)**	0.016	8.577*** (1.792) **	0.032	10.327*** (3.295) ***
tas_12p5_15	0.010	8.498*** (1.992)**	0.013	10.827*** (2.653) ***	0.008	3.248*** (0.852)
tas_15_17p5	0.017	17.117*** (4.636)***	0.019	17.759*** (3.293) ***	0.014	6.301*** (2.026) **
tas_17p5_20	0.015	14.451*** (2.948)***	0.019	18.798*** (3.112) ***	0.005	2.202** (0.565)
tas_20_22p5	0.006	7.886*** (2.628)***	0.014	15.460*** (3.780) ***	-0.001	-0.299 (-0.110)
tas_25_27p5	-0.003	-4.021*** (-0.896)	-0.005	-7.0346*** (-1.504)	0.015	4.419*** (1.416)
tas_27p5_30	-0.000	-0.248 (-0.073)	-0.008	-8.042*** (-1.648) *	0.026	4.382*** (1.691) *
tas_g30	-0.002	-1.852* (-0.353)	0.004	3.353*** (0.433)	0.016	0.792 (0.559)
p_5lo	-0.009	-6.164*** (-1.827)**	0.003	1.458 (0.554)	0.005	0.950 (0.338)
p_5_10	-0.006	-3.526*** (-1.749)**	-0.004	-2.102** (-1.119)	0.018	3.272*** (1.656) *
p_15up	0.018	10.533*** (2.601)***	0.0144	6.593*** (1.679) *	-0.001	-0.192 (-0.109)

$* p < 0.1; ** p < 0.05; *** p < 0.01$

(e) **pDSSAT**

T, P bins	Maize (Coeff diff)	T	Soybeans (Coeff diff)	t	Wheat (Coeff diff)	t
tas_7p5lo	0.012	6.584*** (1.350)	0.011	2.418** (0.456)	0.000	-0.233 (-0.088)
tas_7p5_10	0.010	6.025*** (1.265)	0.014	3.836*** (0.884)	0.014	4.902*** (1.868) *
tas_10_12p5	0.009	7.405*** (1.875)**	0.004	1.457*** (0.422)	0.015	6.274*** (2.186) **
tas_12p5_15	0.006	6.622*** (1.799)**	-0.008	-3.997 (-0.800)	0.002	0.974 (0.352)
tas_15_17p5	0.001	1.316*** (0.308)	-0.011	-5.509*** (-1.117)	0.009	5.0493*** (1.907) *
tas_17p5_20	0.007	8.705*** (2.230)**	-0.001	-0.676 (-0.148)	0.005	3.041*** (1.090)
tas_20_22p5	0.003	4.218*** (1.895)*	0.006	4.451*** (0.966)	0.004	2.130*** (0.759)
tas_25_27p5	-0.003	-3.679*** (-1.470)	-0.020	-15.169*** (-4.568) ***	0.027	8.022*** (2.840) ***
tas_27p5_30	0.006	6.349*** (1.657)*	-0.012	-8.231*** (-2.160) **	0.021	3.468*** (1.361)
tas_g30	0.000	0.104 (0.027)	-0.026	-14.603*** (-1.731) *	0.058	3.078*** (2.210) **
p_5lo	-0.006	-4.697*** (-1.405)	-0.054	-18.059*** (-6.630) ***	0.010	2.925*** (1.198)
p_5_10	-0.004	-2.907*** (-1.566)*	-0.014	-4.291*** (-1.739) *	0.016	3.755*** (2.385) **
p_15up	0.009	5.756*** (1.885)*	0.014	4.061*** (1.493)	0.0152	2.788*** (1.797) *

(f) **PEGASUS**

tas_7p5lo	-0.007	-3.913*** (-0.781)	-0.056	-17.536*** (-2.172) **	-0.017	-6.157*** (-1.199)
tas_7p5_10	-0.020	-11.593*** (-2.676)***	-0.021	-7.791*** (-1.886) *	-0.012	-4.099*** (-0.996)
tas_10_12p5	-0.013	-9.563*** (-2.276)**	-0.014	-7.192*** (-1.652) *	0.011	4.340*** (1.316)
tas_12p5_15	-0.010	-10.809*** (-2.116)**	-0.016	-14.101*** (-2.221) **	-0.001	-0.765 (-0.296)
tas_15_17p5	-0.005	-6.872*** (-1.402)	-0.006	-6.292*** (-1.137)	0.008	3.509*** (1.152)
tas_17p5_20	-0.001	-1.956*** (-0.448)	-0.001	-1.306 (-0.326)	0.008	3.805*** (1.157)
tas_20_22p5	0.000	-0.416*** (-0.126)	-0.001	-2.259** (-0.658)	0.008	3.809*** (1.410)
tas_25_27p5	-0.003	-4.365*** (-1.338)	-0.004	-4.998*** (-1.765) *	0.022	6.280*** (2.056)**
tas_27p5_30	0.006	6.139*** (1.835)*	0.002	2.331** (0.512)	-0.003	-0.456 (-0.146)
tas_g30	-0.004	-3.794*** (-0.883)	-0.001	-0.563 (-0.134)	0.046	2.485** (1.693)*
p_5lo	0.004	2.935*** (0.938)	0.014	7.655*** (2.844) ***	0.010	2.608** (0.998)
p_5_10	0.000	0.451 (0.264)	0.010	5.128*** (2.947) ***	0.003	0.679 (0.410)
p_15up	-0.003	-1.879* (-0.656)	0.003	1.566 (0.560)	0.014	2.665** (1.162)

$* p < 0.1; ** p < 0.05; *** p < 0.01$

(g) **Multi-GGCM**

T, P bins	Maize (Coeff diff)	T	Soybeans (Coeff diff)	t	Wheat (Coeff diff)	t
tas_7p5lo	0.022	15.798*** (2.291)**	0.012	7.301*** (1.082)	0.004	2.013** (0.548)
tas_7p5_10	0.008	6.082*** (1.084)	0.005	4.089*** (0.695)	0.010	4.062*** (1.327)
tas_10_12p5	0.011	11.623*** (2.374)**	0.012	10.623*** (2.373)**	0.019	9.122*** (3.156)**
tas_12p5_15	0.008	11.104*** (2.728)***	0.005	7.000*** (1.661)*	0.005	3.167*** (1.199)
tas_15_17p5	0.008	12.405*** (2.583)***	0.007	10.719*** (2.490)***	0.012	7.014*** (2.808)**
tas_17p5_20	0.009	16.146*** (3.470)***	0.007	13.917*** (3.098)***	0.009	5.265*** (1.788)*
tas_20_22p5	0.004	7.808*** (2.964)***	0.005	9.263*** (2.560)***	0.007	3.615*** (1.490)
tas_25_27p5	-0.003	-5.794*** (-1.645)*	-0.007	-13.102*** (-4.670)***	0.024	8.455*** (2.703)***
tas_27p5_30	0.003	6.133*** (1.473)	-0.003	-4.329*** (-0.831)	0.021	3.829*** (1.538)*
tas_g30	0.001	0.673 (0.161)	0.002	2.530** (0.686)	0.055	3.153*** (2.153)**
p_5lo	-0.003	-3.152*** (-0.887)	-0.004	-4.613*** (-1.381)	0.006	1.877* (0.794)
p_5_10	-0.003	-3.097*** (-1.557)*	-0.002	-1.286 (-0.695)	0.009	2.263** (1.484)
p_15up	0.010	7.916*** (2.113)**	0.009	7.337*** (2.692)***	0.015	3.072*** (1.760)*

$* p < 0.1; ** p < 0.05; *** p < 0.01$

Table S9. Mid (2033~2065)- and end-century (2067~2099) (in parenthesis) % change in aggregated production under RCP 8.5 warming scenario simulated by HadGEM2-ES, due to extreme high temperature ($T > 30\ °C$) days. The projected % change in production is aggregated for the sample of counties shown in maps of Fig. 5 (main text).

GGCM	Maize	Soybeans	Wheat
GEPIC	-47% (-72%)	-35% (-55%)	-9% (-52%)
GAEZ-IMAGE	1% (3%)	4% (7%)	0% (-4%)
LPJ-GUESS	-26% (-45%)	-42% (-63%)	-7% (-42%)
LPJmL	-35% (-59%)	-33% (-52%)	-46% (-66%)
pDSSAT	-32% (-54%)	-64% (-86%)	-30% (-35%)
PEGASUS	-38% (-62%)	-40% (-61%)	-37% (-44%)
Multi-GGCM	-32% (-53%)	-35% (-56%)	-33% (-42%)
USDA	-32% (-54%)	-39% (-60%)	-53% (-73%)

S8. Average change in exposure across HadGEM2-ES temperature and precipitation bins in RCP 8.5 scenario, relative to historical (1981-2004)

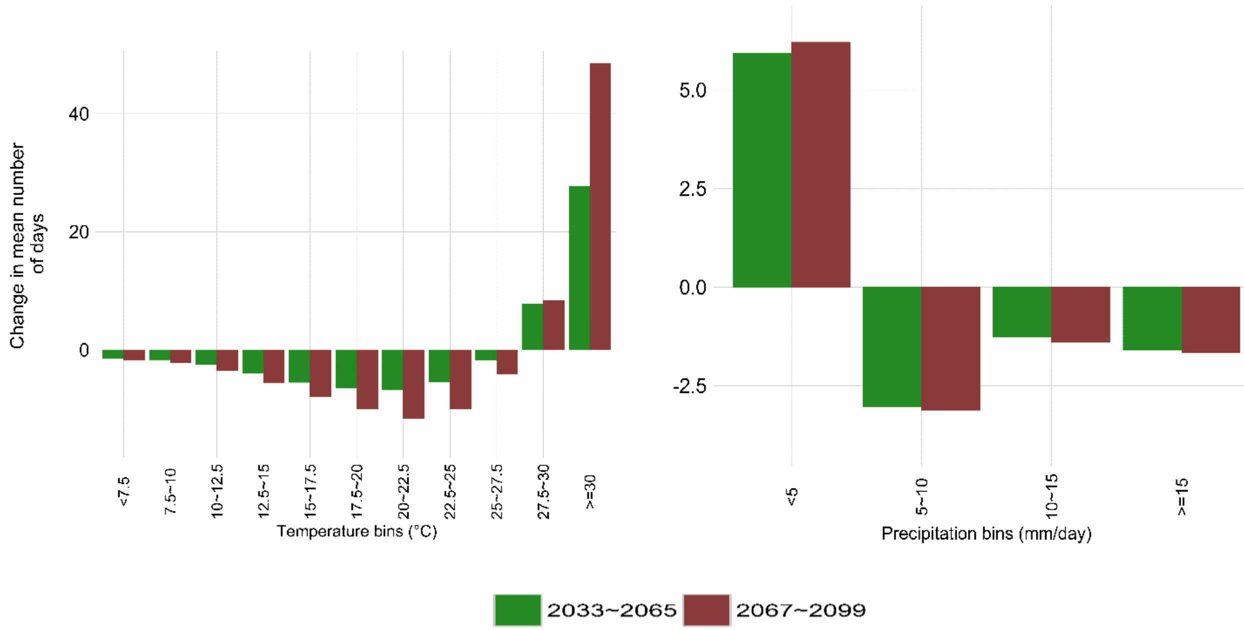

Fig. S6. Change in distribution of HadGEM2-ES temperature and precipitation bins, for two mean future periods in RCP 8.5 scenario.

The change in number of days is computed by first averaging the number of days (in each bin) in each USDA crop county, for the historical and future periods. The average number of days (in each bin) are then computed over all counties. The difference is calculated as future period – historical period.

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