Unpacking the climatic drivers of U.S. agricultural yields

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Supporting Materials

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1 Materials and Methods

1.1 Data sources

We rely on county-level crop yield data from USDA/NASS (1981–2017) for six major crops in the United States: maize, soybeans, winter wheat, spring wheat, cotton and sorghum. We use average acreage over the sample period as weight for computing sample-wide climate change impact projections. The analysis is based on a slightly unbalanced panel of rain-fed counties (Fig. S1). We represent crop yields over time in Fig. S2.

Our main analysis estimates intra-seasonal effects of soil moisture and temperature, which requires defining a growing season. We define the growing season for every crop as a calendar period that includes the historical timing of planting or emergence as well as maturation or harvest (Fig. S3). This corresponds to April–September for maize, soybeans, cotton and sorghum, April–August for spring wheat, and October–June for winter wheat. We considered models accounting matching environmental conditions to phenological crop stages and results remain very similar. However, we favored models based on calendar growing seasons to simplify exposition.

Unlike meteorological data, there is no extensive network of soil moisture monitoring stations. We therefore obtain soil moisture data from the Land Surface Models (LSM) in the NLDAS-2 [Xia Youlong et al., 2012]. The NLDAS provides hourly soil moisture for each 1/8th-degree (~14km) for various soil depths (available soil depths vary by LSM) across North America since January 2, 1979. The NLDAS LSMS combine hourly information about multiple atmospheric variables (e.g. precipitation, wind, air temperature, etc.) with biophysical land characteristics (e.g. crop cover, soil type) to derive the state of soil water content over time. We rely on soil moisture for the superficial soil layer (0–10cm) which is the data we find best predicts crop yields (vs. 0–100cm layer, see Figs. S28–29) and that is readily available in future climate projections. This restricted our choice to 3 of the 4 available LSM in NLDAS-2 (NOAH, SAC and MOSAIC). The excluded LSM (VIC) has variable soil layers and we could not obtain measures of soil moisture for the chosen soil layer. To facilitate future comparisons, we chose to represent soil moisture content in SI units of water mass per volume of soil (kg/m$^3$). If we assume that the density of water is 1000 kg/m$^3$ then our measures of moisture content can be directly interpreted in the more familiar unit of millimeters (mm) of water in a meter of soil. For instance, 250 kg/m$^3$ would be equivalent to 250 mm of water in a meter of soil. Brought to the top 0–10cm of soil, this would be 25mm (or 25kg/m$^2$ over that layer, which is the unit used in the NLDAS framework).

Hourly soil moisture fluctuations are highly variable with large peaks following intense rainfall events. The effect of wet soil on crops over a very brief period (measured in hours) should differ from that of a prolonged exposure such as a flood (measured in days or weeks). We therefore chose to aggregate hourly data to a weekly time scale. This is in line with the time scales chosen for the United States Drought Monitor. Weekly NLDAS grid-level observations are aggregated to the county level based on cropland area falling within each grid. These weights are computed from USDA’s 30-m National Cropland Data Layer (CDL, https://nassgeodata.gmu.edu/CropScape/) by computing the average cropland pixels falling within each NLDAS grid in 2008–2014. This procedure yields a cropland-weighted weekly county-level dataset of superficial soil moisture for each LSM across the nation. The weekly variation for each crop over the sample period is represented in Fig. S4. The weekly aggregation also helps to smooth out peaks of moisture content in the superficial layer (0–10cm) following rainfall events, which are not effectively available to plants. Future work could improve on our measure of water availability by representing the amount of water effectively extractable by plants rather than total soil water content.

For temperature and precipitation data we rely on daily and monthly PRISM data for precipitation, maximum, minimum and average temperature from the PRISM Climate Group (http://www.prism.oregonstate.edu), which is available since 1981. Daily temperatures are processed into temperature exposure bins necessary to estimate nonlinear effects of temperature similar to Schlenker and Roberts [2009]. Specifically, we compute the exposure to each 1°C bin from −15 to 50°C in each PRISM grid by assuming a double sine curve passing through the minimum and maximum temperature of consecutive days. Similar to moisture data, the gridded weather data is aggregated up to the county using cropland weights based on the CDL. Figs. S5–6 show the county-level distributions of monthly precipitation and temperature bins. In Fig. S7
we show the aggregate growing-season distributions of these variables used in the traditional model that assumes additivity.

### 1.2 Regression models

We develop a statistical panel model to estimate the nonlinear and time-varying effects of soil moisture and temperature on crop yield throughout the growing season. The functions $f(m,p)$ and $g(h,p)$ capture the intra-seasonal effects by representing the marginal yield response to soil moisture level $m$ or temperature $h$ at each level of season progress $p$. The logged yield $y_{it}$ in county $i$ and year $t$ can be represented generally as:

$$y_{it} = \int\int f(m,p)\phi_{it}(m,p)d(m)d(p) + \int\int g(h,p)\gamma_{it}(h,p)d(h)d(p) + \psi(t) + \alpha_i + \epsilon_{it}$$

where $\phi_{it}(m,p)$ describes the distribution of soil moisture content and $\gamma_{it}(h,p)$ the distribution of temperature at each level of the growing season. $\psi(t)$ captures a state-level quadratic time trend and $\alpha_i$ is a county fixed effect. We also consider a linear state-level time trend and obtain similar results (Fig. S41—43). The inclusion of $\psi(t)$ and $\alpha_i$ means that the parameters in the model are estimated off the year-to-year fluctuations around the state-level trend in environmental variables at different points of the growing season. This avoids confounding yields with time-invariant omitted variables that may correlate with soil moisture or temperature.

The equation above cannot be estimated due to the integrals. We therefore approximate the soil moisture $f(m,p)$ and temperature $g(h,p)$ yield response functions with a bivariate tensor-product or “2-way” natural cubic spline. This requires we discretize the $\phi_{it}(m,p)$ and $\gamma_{it}(h,p)$ distributions into 2-dimensional (2-D) bins for estimation. Our “progress” bins are simply either weeks for soil moisture or months for temperature. Our “variable level” bins are equally-spaced for soil moisture (50 bins from 0 to 500 kg/m$^3$) and temperature (66 bins from $-15$ to 50 °C). We obtain 2-D binned datasets by computing the time spent in each 2-D bin. To facilitate comparison across crops, we normalize the growing season length to percentages. Prior to the regression analysis, soil moisture bins are aggregated at each tail below 100 and above 350 kg/m$^3$ and temperature bins are aggregated below 0°C and above 35°C. This avoids relying on bins with very little exposure, which leads to noisy estimates for extreme bins.

The 2-way spline is estimated based on a transformed dataset of the 2-D binned data, which is post-multiplied by a 2-D B-spline basis matrix. This is a bi-dimensional generalization of previous work estimating non-linear effects over a single dimension. The 2-D B-spline basis matrix is constructed by performing the outer product of each pair of columns of the individual one-dimensional B-spline matrices of each variable (progress and moisture).

Our statistical model can be specified with varying degrees of flexibility in the “season progress” and “variable level” dimensions so as to approximate the true soil moisture and temperature response surfaces. To choose the degrees of freedom in the progress and level dimensions for the soil moisture and temperature response surfaces we conduct a grid search where we independently vary the flexibility of the model and assess the out-of-sample prediction accuracy (Fig. S44). This prediction accuracy is measured based on the reduction in RMSE relative to a model without environmental variables and based on a 10-fold cross-validation. The cross-validation routine consists in splitting years into 10 random folds and estimating a given model with 9 folds but one, and computing the out-of-sample RMSE of the prediction for the excluded year. We repeat this procedure until every fold is excluded exactly once, and we calculate the average RMSE across these repetitions for that model.

In general, models with too little or too much flexibility exhibit lower prediction accuracy. To favor relatively parsimonious models, we choose levels of model flexibility for which subsequent increases in degrees of freedom do not improve model fit by more than 5 percent. While the 10-fold cross-validation already penalizes models with greater complexity, our approach avoids selecting models that are noticeably more flexible but do not improve model fit or change impact projections much. The primary goal is to simplify the exposition and interpretation of response surfaces in Fig. 1. In Figs. 45—47, we show that the findings of the paper remain fairly robust to more flexible specifications for both intra-seasonal soil moisture and temperature effects.
To illustrate the construction of the regression data, consider the case of the soil moisture response surface for maize (Fig. 1A, maize sub-panel). For this case we set 4 and 3 degrees of freedom for the “progress” and “moisture level” dimensions, respectively (see Fig. S44A, maize sub-panel). This corresponds to 3 and 2 interior knots in each of these two dimensions. The growing season for maize spans from April to September, which corresponds to 27 weeks of soil moisture data or 27 “progress” bins. As stated above, the spline for “progress” has 4 degrees of freedom, so it yields a $27 \times 4$ basis matrix. Similarly, we have 26 moisture bins (100 to 350 kg/m$^3$, in increments of 10). The spline for “moisture level” has 3 degrees of freedom, so it yields a $26 \times 3$ basis matrix. The corresponding 2-D basis spline resulting from the column-wise outer products of these 2 basis matrices has a dimension of $(27 \times 26)$ by $(4 \times 3) = 702$ by 12. The 702 rows correspond to the 702 2-D bins of the data described above. Therefore, post-multiplying the data by this 2-D basis spline leads to a regression dataset that has only 12 soil moisture-progress variables and parsimoniously summarizes the 2-dimensional “interactions” between the progress and moisture indices. Estimating the intra-seasonal effects for temperature follows an analogous procedure. Once the model is estimated, one can recover the marginal effects by pre-multiplying the vector of estimated coefficients with the 2-D basis spline to obtain marginal effects evaluated at each 2-D bin, which approximates $f(m, p)$ and $g(h, p)$.

Throughout the paper we contrast the results of our preferred model with those of a traditional model that assumes temperature exposure and precipitation are additive over the growing season. This statistical model accounts closely follows ref. 9. However, we model temperature effects over the growing season with a natural cubic spline (Fig. S10) rather than an 8th degree polynomial. We show how changing the flexibility of this model changes the prediction accuracy in Fig. S48, where we highlight with solid circles the chosen levels of flexibility. We find this specification yields more stable response functions. Results, nonetheless, remain very similar whether temperature effects are modeled with a polynomial, a spline or step functions. Moreover, the traditional model includes linear and quadratic terms for total precipitation over the growing season. This is a common specification in the literature.

We explore multiple variations of our statistical model, including using soil moisture data from alternative LSMs (Figs. S21–27) and considering soil moisture data for different soil layers (Figs. S28–29). The main analysis is based on the NOAH model, which is the LSM that best predicts crop yield data out of sample (Fig. S21). Unsurprisingly, this coincides with the LSM that best matches soil moisture observations [Xia et al. 2012].

At various points throughout the paper we also refer to a critical month of the growing season (see Fig. 3, Figs. S11–12 and Tab. S1). We identify the critical month of the growing season for each as a month that is very sensitive to moisture change. These can be found by inspection in Fig. 1 for maize (July), soybeans (August), winter wheat (March), spring wheat (June), cotton (July) and sorghum (July). As expected, these months typically coincide with key crop stages (Fig. S3). We also show that our findings are robust to slightly shorter and longer growing seasons (Figs. S49–54).

Throughout the paper we present measures of uncertainty for our statistical crop yield model. These are reflected in response functions to moisture and temperature (e.g. Fig. 1) and climate change impacts (e.g. Fig. 4). These are computed based on a block bootstrapping procedure whereby we sample years of the data with replacement (R=1,000). This procedure preserves the underlying spatial and contemporaneous dependence in the errors terms in the panel model. We considered additional strategies for the bootstrap including blocking at the county, state-by-year and state-by-2-year (following Moore and Lobell [2014]), but we favor blocking by year which yields more conservative estimates. The impacts for these alternative blocking strategies are shown in Figs. S55–57.

### 1.3 Climate and moisture projections

Future projections of changes in soil moisture, temperature, and precipitation are derived from models archived as part of the Climate Model Intercomparison Project Phase 5 (CMIP5) project, and include the same collection of General Circulation Model (GCM) simulations used for the 5th Intergovernmental Panel on Climate Change (IPCC). Native GCM spatial resolution tend to be between 50 and 200 km, which is much coarser than required for our estimates of crop yields. We therefore applied a modified version of the downscaling method in Mosier et al. [2014]. In the original
implementation of this downscaling method, coarse resolution GCM anomalies are first interpolated to the finer scale resolution of an observational target grid. Next, these interpolated anomalies are added to historical climatologies, yielding future trajectories at high spatial resolution with changes in the long term mean and variability that are consistent with the coarse resolution of the GCM output.

In our downscaling approach, the fine resolution target are the 1/8th-degree (~14km) NLDAS and 4km PRISM grids. The coarse resolution GCM data originate from the IPCC models with surface soil moisture (mrsos), surface air temperature (tas), and precipitation (pr) fields available at monthly and weekly timescales, and for both historical and climate change scenarios. This list of models is restricted to the following subset of all CMIP5 GCMs: CNRM-CM5, FGOALS-g2, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, HadGEM2-CC, HadGEM2-ES, INM-CM4, IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC5, MIROC-ESM-CHEM, MIROC-ESM, MRI-CGCM3, and MRI-ESM1. Several models include multiple ensemble members, and all include simulations of different RCPs. Here, we use the RCP 2.6, 4.5, 6.0 and 8.5 scenarios, which represent total net increase in long-wave radiative forcing of 2.6, 4.5, 6.0 and 8.5 W/m$^2$ by the end of the 21st Century, respectively.

Our initial step is to compute historical “reference” climatologies for each variable at weekly and monthly timescales from each CMIP5 model at its native resolution using the period (of the model) from 1950−2000. Likewise, we compute future climatologies from each GCM for the periods between 2025−2075 and 2050−2100 for each RCP and ensemble. Next, we compute changes in model mean ($\Delta \mu$) according to $\Delta \mu = \mu_{\text{future}} - \mu_{\text{historical}}$ for temperature (tas), and $\Delta \mu = (\mu_{\text{future}} - \mu_{\text{historical}})/\mu_{\text{historical}}$ for soil moisture (mrsos) and precipitation (pr). The changes in temperature are therefore to be regarded as actual differences in the mean and variance of the quantity itself, whereas the changes in precipitation and soil moisture are fractional increases or decreases relative to historical climatology. Our choice to use fractional changes for these two quantities stems from widespread recognition throughout in climate science that precipitation and soil moisture mean changes are likely less robust than relative changes within each model compared to its own climatology. Changes in mean climatology are computed from each model at each grid point for all ensemble members and scenarios at model resolution prior to interpolation. The final two steps in our downscaling procedure are to (i) interpolate the modified climatologies of the future to the target grid, and then (ii) apply those changes to NLDAS or PRISM climatology.

1.4 Climate change impacts on crop yields

Climate change impacts for each county are computed by multiplying the estimated environmental parameters in the regression model for by the projected change in climatology between the reference (1950−2000) and projection period (2025−2075 or 2050−2100) for variables reconfigured in their transformed regression format. Because yields are logged, we report projected changes in crop yields for a vector of counties as $\Delta \hat{Y} = 100(e^{\Delta X\hat{\beta}} - 1)$, where $\hat{\beta}$ are the estimated environmental coefficients and $X$ is a matrix of the regression data for the environmental variables (e.g. transformed variables for soil moisture, temperature, and precipitation). Note that $\Delta X = X_{\text{future}} - X_{\text{historical}}$ represents the change in environmental variables as they enter the regression model. That means that for variables like temperature or soil moisture, these need to be reconfigured from their original form (e.g. 2-D bins) into regression form, prior to computing the changes in the climatology. Finally, sample-wide impacts are obtained by weighting county-level impacts by the historical crop acreage (1981−2017).

2 Additional Checks

2.1 Potential underestimation of water stress in climate change impacts

Our analysis indicates that accounting for intra-seasonal soil moisture effects reduces the contribution of direct temperature effects in driving climate change impacts (Fig. 5). Our study relies on state-of-the-art land surface data from the NLDAS,
which provides fine-scale soil moisture information from various LSMs for the superficial soil layer (0–10cm). However, some of these LSMs match observations better than others depending on the region (17). This could imply that adopting less accurate measures of soil moisture may not only deteriorate prediction accuracy of crop yields but also point to an increased role of direct temperature effects, and a smaller role of soil moisture change, in driving climate change impacts. We thus analyze how statistical crop yield models based on soil moisture data derived from competing LSMs predict crop yields. Fig. S21 shows that statistical models based on the NOAH soil moisture data, which we rely upon for the main analysis in this study, consistently outperform competing models. This suggests that the NOAH LSM provides the best approximation of soil moisture content for our sample. This largely coincides with the validation of NLDAS data (17).

We subsequently examine how using less accurate soil moisture data affects our findings. For the two competing LSMs, MOSAIC and SAC, we report the estimates of intra-seasonal moisture and temperature effects, the associated climate change impacts and their decomposition by variable type (Figs. S22–27). The intra-seasonal moisture effects show some qualitative similarities and climate change impact projections seem comparable to those of our preferred model based on the NOAH data (Figs. 1A and 4A). However, the decomposition of impacts shows a considerably lower role of soil moisture for models based on MOSAIC and SAC moisture data relative to models based on NOAH moisture data.

In essence, using less accurate soil moisture data for the historical statistical analysis ultimately reduces the role of soil moisture change in driving climate change impacts on future crop yields. Because our preferred moisture data still likely remains an imprecise proxy for the true level of moisture content, we hypothesize our current implementation possibly underestimates the role of soil moisture change in explaining future crop yield distributions.

2.2 Results based on moisture from deeper soil layer

The root system of field crops extends well beyond the superficial layer (0–10cm) that we rely upon for the analysis. We thus explore the prediction accuracy of soil moisture data for the 0–100cm soil layer. We summarize the results in Fig. S28 for four competing LSMs. Again, the NOAH LSM provides the highest predictive accuracy for all crops but sorghum. Interestingly, moisture content for the 0–100cm layer does not consistently improve prediction accuracy relative to the superficial 0–10cm layer. This result is somewhat surprising but may simply reflect that moisture content of the 0-100cm soil layer may be measured with more error over our sample region.

Unfortunately, climate change projections of soil moisture content for the 0–100cm soil layer are not readily available, so we cannot compute the associated climate change impacts. Nonetheless, we report the soil moisture and temperature response functions for the preferred specification based on the 0–100cm NOAH LSM data in Fig. S29. The soil moisture response surface is qualitatively similar to that based on the 0–10cm layer in Fig. 1A, suggesting that modeled historical soil moisture fluctuations across these two soil layers are highly correlated. Unless climate change leads to sizeable differential changes in moisture across soil layers, impact projections based on superficial and deeper layers should remain comparable.

2.3 Limitations of precipitation in capturing future water stress

A key finding of our study is that accounting for intra-seasonal effects of soil moisture improves model fit and points to a greater role of water stress and a smaller (though still large) role of direct temperature effects in future climate change impacts. We explore whether applying our statistical technique of estimating intra-seasonal environmental effects to precipitation (instead of soil moisture), leads to comparable findings. Note that moisture and temperature variables are constructed as measures of exposure to certain levels of each variable, whereas precipitation measures a flow of water, thus the interpretation of marginal effects is different. This exercise nonetheless allows the effect of monthly precipitation levels to vary smoothly over the growing season.

Similar to the other variables, out-of-sample prediction accuracy improves when allowing this intra-seasonal flexibility in precipitation effects (Fig. S30). Relative to a model with just linear and quadratic terms of total growing season precipitation, accounting for intra-seasonal precipitation effects alone improves model fit for cotton (+258%), maize (+155%), winter wheat (+153%), soybeans (+152%) and sorghum (+29%), but reduces it for spring wheat (−9%), a short-season crop. On average, these improvements are smaller but remain comparable to the those from adopting
intra-seasonal moisture effects. To analyze the implications of accounting for intra-seasonal effects of precipitation instead of moisture, we estimate an alternative model that replaces moisture in our preferred model with precipitation. The resulting response surfaces are shown in Figs. S31–33. In general, extreme levels of precipitation are detrimental and low precipitation levels are particularly damaging around the middle of the growing season. We compute the associated climate change impacts and their decomposition by variable type (Fig. S34). The overall impacts appear comparable to our proposed model, except for a few projections (Tab. S5).

However, under this alternative model, precipitation still plays a relatively minor role in driving climate change impacts during the middle and the end of the century (Fig. S35). Specifically, precipitation explains, on average, 5.2, 6.9, 4.6, 3.5, 3.5 and 3.3% of total impacts during the end of the century for maize, soybeans, winter wheat, spring wheat, cotton and sorghum, respectively. This is greater than the role of precipitation in the traditional model based on additive season-long variables, but remains 71 to 86 percent lower than the role of soil moisture in explaining overall impacts in our preferred approach.

In summary, allowing for intra-seasonal effects of precipitation improves model fit for historical yields but does not substantially increase the contribution of precipitation change to future yield distributions under climate change. This suggests that precipitation variables, even when allowing for intra-seasonal variation in its effects, have limited skill in predicting future water stress for crop yields. Our preferred specification based on soil moisture suggests a much greater role for water resources in driving future yield distributions. Soil moisture accounts for the intensity of rainfall events as well as the evaporative demand of higher temperature, so the variable appears better suited for explicitly capturing water-related stresses than precipitation.

2.4 Temporal and regional robustness

A critical question for climate change adaptation is whether new agricultural technologies are reducing the sensitivity of crop yields to climatic variations. New crop varieties have led to higher yields but may have also provided greater resistance to drought or heat stresses. To verify this, we first assess the evolution of crop yield sensitivities to soil moisture and temperature by estimating our model for an early (1981–1999) and a late period (2000–2017) and then compute the associated climate change impacts (Figs. S36–37). If we detect any differences in projected impacts, these could stem from the evolution of climatic sensitivities associated with recent technological or management changes. However, we find very small differences (Tab. S6). Only in a handful of climate projections for sorghum, do we perceive that recent climatic sensitivities could lead to larger projected impacts.

We also find regional differences in crop yield sensitivities to environmental conditions appear relatively small. Farmers are likely to adopt the best-suited cultivars for their current agro-climatic situation. Thus, crop yields in regions with different climates may exhibit distinct sensitivities to environmental conditions. To consider this possibility, we estimate separate models and analyze climate change impacts for two equally-sized northern and southern subsamples for each crop. We find the sensitivities to soil moisture and temperature are qualitatively similar across subsamples (Figs. S38–39). Similarly, yield impacts from uniform changes in soil moisture and temperature during the critical month of the growing season for each crop appear similar (Fig. S40). In addition, we find that climate change projections based on CMIP5 are similar, with some projections pointing to a somewhat more pessimistic outlook for soybeans in the southern sample and for sorghum in the northern sample (Tab. S7).
Supplementary Figures
Figure S1: Study sample. A. Number of county-level observations (years) by crop in the complete dataset. B. Average share of the county harvested area that is irrigated, based on the US Census of Agriculture for 1997, 2002, 2007 and 2012, which has the greatest coverage. When missing, we supplement this information with survey data from USDA/NASS for 1981-2012. The combined information is depicted. C. Our designation of “irrigated” and “rain-fed” counties. Counties are considered rain-fed when less than 50% of average harvested acreage is irrigated. When information regarding the irrigation share is unavailable for a county with production data, we consider it irrigated if located to the west of the 100th meridian West, or rain-fed if located to the east of that same meridian. The 100th meridian West is highlighted with a vertical black line. Results are fairly insensitive to a lower irrigation threshold (e.g. 10%) given the relatively small share of counties within irrigation shares in the 10-50% range.
Figure S2: Crop yields over time. Each panel provides a boxplot with the yearly crop yield distribution for each crop for all rain-fed counties in the sample. The solid central line represents the median. The upper and lower box boundaries represent the first and third quartiles. Whiskers extend to 1.5 times the interquartile (IQR) range beyond the box hinge. Depicted symbols extend beyond 1.5 IQR.
Figure S3: Growing seasons. Double arrows indicate the growing season for each crop. The histograms represent the distribution of when 50% of acreage within a state-year reaches a particular crop stage (e.g. flowering) or practice (e.g. planting) in the sample over. The growing seasons encompass most stages.
Figure S4: Weekly moisture distribution. Each panel provides a boxplot with the weekly distribution of soil moisture over the sample period (1981-2017) for all rain-fed counties for each crop. The solid central line represents the median. The upper and lower box boundaries represent the first and third quartiles. Whiskers extend to 1.5 times the interquartile (IQR) range beyond the box hinge. Depicted symbols extend beyond 1.5 IQR. The red double arrows indicate the growing seasons.
Figure S5: Monthly precipitation moisture distribution. Each panel provides a boxplot with the monthly distribution of precipitation over the sample period (1981-2017) for all rain-fed counties for each crop. The solid central line represents the median. The upper and lower box boundaries represent the first and third quartiles. Whiskers extend to 1.5 times the interquartile (IQR) range beyond the box hinge. Depicted symbols extend beyond 1.5 IQR. The red double arrows indicate the growing seasons.
Figure S6: Monthly distributions of temperature. Exposure to temperature bins over the growing season. Each panel provides a boxplot with the seasonal distribution at each temperature bin over the sample period (1981-2017) for all rain-fed counties for a given crop. The solid central line represents the median. The upper and lower box boundaries represent the first and third quartiles. Whiskers extend to 1.5 times the interquartile (IQR) range beyond the box hinge. Depicted symbols extend beyond 1.5 IQR. The months represented in red fall within the growing season.
Figure S7: Distributions of growing season weather variables. A. Exposure to temperature bins over the growing season. Each panel provides a boxplot with the seasonal distribution at each temperature bin over the sample period (1981-2017) for all rain-fed counties for a given crop. The solid central line represents the median. The upper and lower box boundaries represent the first and third quartiles. Whiskers extend to 1.5 times the interquartile (IQR) range beyond the box hinge. Depicted symbols extend beyond 1.5 IQR. B. Histogram of seasonal precipitation.
Figure S8: Effects of soil moisture variation on crop yields for the proposed model at different points of the growing season. Each panel presents the bootstrapped replicates of the response functions for a given crop and a particular level of season progress. The dark solid line represents the mean response and the confidence band represents a 95% percentile bootstrap confidence interval. The underlying moisture density for each crop and season progress level is represented in green.
Figure S9: Effects of temperature exposure on crop yields for the proposed model at different points of the growing season. Each panel presents the bootstrapped replicates of the response functions for a given crop and a particular level of season progress. The dark solid line represents the mean response and the confidence band represents a 95% percentile bootstrap confidence intervals. The underlying moisture density for each crop and season progress level is represented in red.
Figure S10: Effect of temperature exposure on crop yields for the traditional model. Each panel presents the bootstrapped replicates of temperature response functions for a given crop. The dark solid line represents the mean response and the confidence band represents a 95% percentile bootstrap confidence intervals. The underlying growing-season density of temperature exposure is represented in grey below each response function.
Figure S11: Crop yield projections from uniform changes during critical month of growing season for the traditional model. Weather variables correspond to the pluri-monthly growing season adopted in the main analysis. The identification of the critical month for maize (July), soybeans (August), winter wheat (March), spring wheat (June), cotton (July) and sorghum (July) is discussed in Methods.
Figure S12: Crop yield projections from uniform changes during critical month of growing season for the traditional model. Weather variables are restricted to the critical month. The identification of the critical month for maize (July), soybeans (August), winter wheat (March), spring wheat (June), cotton (July) and sorghum (July) is discussed in Methods.
Figure S13: Climate change impact projections on United States crop yields for the proposed and traditional models during the middle of the century. Each dot represents a particular GCM in CMIP5 for the middle of the century (2025-2075). Vertical lines around each dot represents the 95% confidence interval based on a block bootstrap procedure whereby years of the data are sampled with replacement. The horizontal solid black line and the colored bands correspond to the mean and +/- two standard deviation of each ensemble, respectively. 

A. Proposed model accounting for intra-seasonal variation in soil moisture and temperature effects. 

B. Traditional model with constant intra-seasonal effects of precipitation and temperature.
Figure S14: Decomposition of climate change impact projections on United States crop yields into water-related variables (precipitation or moisture) and temperature for the middle of the century (2025-2075). Each colored bar represents the CMIP5 ensemble mean contribution to yield impacts for each type of variable. Each dot represents the contribution of the variable to yield impact for a particular GCM. A. Proposed model accounting for intra-seasonal effects of soil moisture and temperature. B. Traditional model with additive effects of precipitation and temperature.
Figure S15: Mid-century climate change impacts correspondence between the proposed model and a traditional model. Each circle represents a sample-wide impact corresponding to particular GCM of the ensemble for the middle of the century (2025-2075). The cloud of points represents county-level correspondences.
Figure S16: End-of-century climate change impacts correspondence between the proposed model and a traditional model. Each circle represents a sample-wide impact corresponding to particular GCM of the ensemble for the middle of the century (2050-2100). The cloud of points represents county-level correspondences.
Figure S17: Mid-century climate change impact decomposition for the traditional model. Each circle represents a sample-wide impact decomposition corresponding to particular GCM of the ensemble for the middle of the century (2025-2075). The cloud of points represents county-level decompositions. (Unit: pp=percentage points)
Figure S18: End-of-century climate change impact decomposition for the traditional model. Each circle represents a sample-wide impact decomposition corresponding to particular GCM of the ensemble for the end of the century (2050-2100). The cloud of points represents county-level decompositions. (Unit: pp=percentage points)
Figure S19: Mid-century climate change impact decomposition for the proposed model. Each circle represents a sample-wide impact decomposition corresponding to particular GCM of the ensemble for the middle of the century (2025-2075). The cloud of points represents county-level decompositions. (Unit: pp=percentage points).
Figure S20: End-of-century climate change impact decomposition for the proposed model. Each circle represents a sample-wide impact decomposition corresponding to particular GCM of the ensemble for the end of the century (2050-2100). The cloud of points represents county-level decompositions. (Unit: pp=percentage points).
Figure S21: Reduction in RMSE for alternative LSMs for the 0-10cm soil layer. The reduction is computed relative to a model without soil moisture variables. The individual bars correspond to the degrees of freedom (1 through 8) for the 2-dimensional spline. The same degrees of freedom are chosen for the season progress and the soil moisture level dimensions. The analysis is restricted to 1980-2014 so that the same number of years analyzed across every crop-LSM combination.
Figure S22: Intra-seasonal effects of soil moisture and temperature on crop yields throughout the growing season based on the MOSAIC LSM. Information regarding the statistical uncertainty is captured with 1,000 bootstrap replicates blocked by year. Intra-seasonal effects of A. soil moisture and B. temperature.
Figure S23: Intra-seasonal effects of soil moisture and temperature on crop yields throughout the growing season based on the SAC LSM. Information regarding the statistical uncertainty is captured with 1,000 bootstrap replicates blocked by year. Intra-seasonal effects of A. soil moisture and B. temperature.
Figure S24: Climate change impact projections on United States crop yields based on the MOSAIC LSM. Each dot represents a particular GCM in CMIP5. Vertical lines around each dot represents the 95% confidence interval based on a block bootstrap procedure whereby years of the data are sampled with replacement. The horizontal solid black line and the colored bands correspond to the mean and +/- two standard deviation of each ensemble, respectively. Climate projections for **A.** the middle of the century (2025-2075) and **B.** the end of the century (2050-2100).
Figure S25: Climate change impact projections on United States crop yields based on the SAC LSM. Each dot represents a particular GCM in CMIP5. Vertical lines around each dot represent the 95% confidence interval based on a block bootstrap procedure whereby years of the data are sampled with replacement. The horizontal solid black line and the colored bands correspond to the mean and +/- two standard deviation of each ensemble, respectively. Climate projections for A. the middle of the century (2025-2075) and B. the end of the century (2050-2100).
Figure S26: Decomposition of climate change impact projections on United States crop yields into moisture and temperature for preferred specification based on MOSAIC LSM moisture data. Each colored bar represents the CMIP5 ensemble mean contribution to yield impacts for each type of variable. Each dot represents the contribution of the variable to yield impact for a particular GCM. Projections during the A. middle of the century (2025-2075) and the B. end of the century (2050-2100).
Figure S27: Decomposition of climate change impact projections on United States crop yields into moisture and temperature for preferred specification based on SAC LSM moisture data. Each colored bar represents the CMIP5 ensemble mean contribution to yield impacts for each type of variable. Each dot represents the contribution of the variable to yield impact for a particular GCM. Projections during the A. middle of the century (2025-2075) and the B. end of the century (2050-2100).
Figure S28: Reduction in RMSE for alternative LSMs for the 0-100cm soil layer. 

A. Reduction relative to baseline model. The reduction is computed relative to a model without soil moisture variables. The individual bars correspond to the degrees of freedom (1 through 8) for the 2-dimensional spline. The same degrees of freedom are chosen for the season progress and the soil moisture level dimensions. The analysis is restricted to 1980-2014 so that the same number of years analyzed across every crop-LSM combination.

B. Comparison of RMSE reduction relative to baseline models between model based on 0-10cm soil layer and model based on 0-100cm soil layer. Positive values mean that the 0-100cm model improves model fit relative to models based on the 0-10cm. The bars represent the average changes for all model flexibilities considered in panel A.
Figure S29: Intra-seasonal effects of soil moisture and temperature on crop yields throughout the growing season based on soil moisture data from the NOAH LSM for the 0-100cm soil layer. The model is otherwise identical to that developed in the paper. A. Soil moisture effects and B. Temperature effects.
**Figure S30: Reduction in RMSE for different levels of flexibility for the 2-way spline for precipitation.** The figure presents the out-of-sample root-meansquare error (MSE) reduction relative to a baseline model without environmental variables. The RMSE reductions are presented for each combination of degrees of freedom in the “variable level” and “season progress” dimensions. Higher values (blue) indicate better model predictions. Dashed circles show the model flexibility with the highest reduction in RMSE whereas solid circles indicate the models adopted in the subsequent analysis. The selected models correspond to models for which additional flexibility does not improve out-of-sample prediction accuracy by more than 5%.
Figure S31: Intra-seasonal effects of precipitation and temperature on crop yields throughout the growing season for an alternative model. The response surfaces indicate the marginal effect on crop yield of spending a 1% fraction of the growing season at a specific level of the relevant variable. Dashed lines in each panel represent percentiles and illustrate the underlying historical distribution of the relevant variable in the sample at each point of the growing season. The green and blue circles in the maize sub-panels correspond to levels of exposure in 1985 and 2012, respectively, in McLean County, Illinois, which the largest maize-producing county in the United States. Information regarding the statistical uncertainty is captured with 1,000 block-bootstrap replicates. A. Precipitation effects. B. Temperature effects.
Figure S32: Effects of precipitation change on crop yields at different points of the growing season for an alternative model accounting for intra-seasonal precipitation and temperature effects. Each panel presents the bootstrapped response functions for a given crop and a particular level of season progress. The dark solid line represents the mean response and the confidence band represents a 95% percentile bootstrap confidence intervals. The underlying moisture density for each crop and season progress level is represented in green.
Figure S33: Effects of temperature exposure on crop yields at different progress levels for an alternative model accounting for intra-seasonal precipitation and temperature effects. Each panel presents the bootstrapped response functions for a given crop and a particular level of season progress. The dark solid line represents the mean response and the confidence band represents a 95% percentile bootstrap confidence intervals. The underlying moisture density for each crop and season progress level is represented in red.
Figure S34: Climate change impact projections on United States crop yields based on alternative model accounting for intra-seasonal effects of precipitation and temperature. Each dot represents a particular GCM in CMIP5. Vertical lines around each dot represents the 95% confidence interval based on a block bootstrap procedure whereby years of the data are sampled with replacement. The horizontal solid black line and the colored bands correspond to the mean and +/- two standard deviation of each ensemble, respectively. Climate change impact projections on crop yields for the A. middle of the century (2025-2075) and B. end of the century (2050-2100).
Figure S35: Decomposition of climate change impact projections on United States crop yields into precipitation and temperature for alternative model accounting for intra-seasonal effects of precipitation and temperature. Each colored bar represents the CMIP5 ensemble mean contribution to yield impacts for each type of variable. Each dot represents the contribution of the variable to yield impact for a particular GCM. Projections during the A. middle of the century (2025-2075) and the B. end of the century (2050-2100).
Figure S36: Climate change impact projections on United States crop yields based on 1981-1999 sensitivities to environmental conditions. Impact projections for A. the middle of the century (2025-2075) and the B. end of the century (2050-2100). Impacts are based on a quasi-balanced sample (observations with over 75% of years in the data) to avoid comparing a very different set of counties across the two time periods.
Figure S37: Climate change impact projections on United States crop yields based on 2000-2017 sensitivities to environmental conditions. Impact projections for A. the middle of the century (2025-2075) and the B. end of the century (2050-2100). Impacts are based on a quasi-balanced sample (observations with over 75% of years in the data) to avoid comparing a very different set of counties across the two time periods.
Figure S38: Intra-seasonal effects of soil moisture and temperature on crop yields throughout the growing season based on model for the northern half of the sample. Information regarding the statistical uncertainty is captured with 1,000 bootstrap replicates blocked by year. Intra-seasonal effects of A. soil moisture and B. temperature.
Figure S39: Intra-seasonal effects of soil moisture and temperature on crop yields throughout the growing season based on model for the southern half of the sample. Information regarding the statistical uncertainty is captured with 1,000 bootstrap replicates blocked by year. Intra-seasonal effects of A. soil moisture and B. temperature.
A

Figure S40: Crop yield projections from uniform changes during critical month of growing season for the proposed model fitted to the northern (A) and southern (B) halves of the sample. The identification of the critical month for maize (July), soybeans (August), winter wheat (March), spring wheat (June), cotton (July) and sorghum (July) is discussed in Methods.
Figure S41: Intra-seasonal effects of soil moisture and temperature on crop yields throughout the growing season based on model with linear state-level trend. Information regarding the statistical uncertainty is captured with 1,000 bootstrap replicates blocked by year. Intra-seasonal effects of A. soil moisture and B. temperature.
Figure S42: Climate change impact projections on United States crop yields based on model with linear state-level trend. Each dot represents a particular GCM in CMIP5 for the middle of the century (2025-2075). Vertical lines around each dot represents the 95% confidence interval based on a block bootstrap procedure whereby years of the data are sampled with replacement. The horizontal solid black line and the colored bands correspond to the mean and +/- two standard deviation of each ensemble, respectively. Impact projections for the A. middle of the century (2025-2075) and the B. end of the century (2050-2100).
Figure S43: Decomposition of climate change impact projections on United States crop yields into moisture and temperature for preferred model with a linear state-level time trend. Each colored bar represents the CMIP5 ensemble mean contribution to yield impacts for each type of variable. Each dot represents the contribution of the variable to yield impact for a particular GCM. Projections during the A. middle of the century (2025-2075) and the B. end of the century (2050-2100).
Figure S44: Reduction in RMSE for different levels of flexibility for the 2-way spline for A. soil moisture and B. temperature. The figure presents the out-of-sample RMSE reduction relative to a baseline model without environmental variables. The RMSE reductions are presented for each combination of degrees of freedom in the “variable level” and “season progress” dimensions. Higher values (blue) indicate better model predictions. Rigid specifications (bottom and left rows) have poorer predictions, as do specifications that are too flexible (top right corner). Degrees of freedom are equal to the number of knots minus one in the natural spline. Knots are chosen at regular breaks of the data. Dashed circles show the model flexibility with highest reduction in RMSE whereas solid circle indicate the models adopted in the paper. The preferred models correspond to models for which additional flexibility does not improve out-of-sample prediction accuracy by more than 5%. Grey shaded areas for temperature indicate degrees of freedom that are infeasible because degrees of freedom cannot exceed the number of months or “time bins” in the growing season.
Figure S45: Intra-seasonal effects of soil moisture and temperature exposures on crop yields throughout the growing season based on a more flexible model. For this model we adopt the degrees of freedom (knots) in the 2-dimensional spline for both soil moisture and temperature that lead to the highest prediction accuracy out of sample. Information regarding the statistical uncertainty is captured with 1,000 bootstrap replicates blocked by year. Intra-seasonal effects of A. soil moisture and B. temperature.
Figure S46: Climate change impact projections on United States crop yields based on a more flexible model that maximizes prediction accuracy. For this model we adopt the degrees of freedom (knots) in the 2-dimensional spline for both soil moisture and temperature that lead to the highest prediction accuracy out of sample. Each dot represents a particular GCM in CMIP5 for the middle of the century (2025-2075). Vertical lines around each dot represents the 95% confidence interval based on a block bootstrap procedure whereby years of the data are sampled with replacement. The horizontal solid black line and the colored bands correspond to the mean and +/- two standard deviation of each ensemble, respectively. Impact projections for the A. middle of the century (2025-2075) and the B. end of the century (2050-2100).
Figure S47: Decomposition of climate change impact projections for preferred model with greater flexibility. The model relies on flexibilities in the 2-dimensional spline for both soil moisture and temperature identified in the paper as yielding the highest prediction accuracy out of sample. Each colored bar represents the CMIP5 ensemble mean contribution to yield impacts for each type of variable. Each dot represents the contribution of the variable to yield impact for a particular GCM. A. Middle of the century (2025-2075). B. End of the century (2050-2100).
Figure S48: Reduction in RMSE for different levels of flexibility for the one-way spline for growing-season temperature exposure. The figure presents the out-of-sample root-mean-square error (RMSE) reduction relative to a baseline model without environmental variables. The model imposes constant or additive effects within the growing season so only flexibility in the “level” dimension can be explored. Higher values (blue) indicate better model predictions. Dashed circles show the model flexibility with highest reduction in RMSE whereas solid circle indicate the models adopted in the paper. The preferred models correspond to models for which additional flexibility does not improve out-of-sample prediction accuracy by more than 5%.
Figure S49: Intra-seasonal effects of soil moisture and temperature on crop yields throughout the growing season based on longer growing season. The growing seasons is two months longer than the preferred growing season in the paper. Information regarding the statistical uncertainty is captured with 1,000 bootstrap replicates blocked by year. Intra-seasonal effects of A. soil moisture and B. temperature.
Figure S50: Climate change impact projections on United States crop yields based on longer growing season. The growing seasons is two months longer than the preferred growing season in the paper. Each dot represents a particular GCM in CMIP5 for the middle of the century (2025-2075). Vertical lines around each dot represents the 95% confidence interval based on a block bootstrap procedure whereby years of the data are sampled with replacement. The horizontal solid black line and the colored bands correspond to the mean and +/- two standard deviation of each ensemble, respectively. Impact projections for the A. middle of the century (2025-2075) and the B. end of the century (2050-2100).
Figure S51: Decomposition of climate change impact projections on United States crop yields into moisture and temperature for preferred model based on longer growing season. Each colored bar represents the CMIP5 ensemble mean contribution to yield impacts for each type of variable. Each dot represents the contribution of the variable to yield impact for a particular GCM. Projections during the A. middle of the century (2025-2075) and the B. end of the century (2050-2100).
Figure S52: Intra-seasonal effects of soil moisture and temperature on crop yields throughout the growing season based on shorter growing season. The growing seasons is two months shorter than the preferred growing season in the paper. Information regarding the statistical uncertainty is captured with 1,000 bootstrap replicates blocked by year. Intra-seasonal effects of A. soil moisture and B. temperature.
Figure S53: Climate change impact projections on United States crop yields based on shorter growing season. The growing seasons is two months shorter than the preferred growing season in the paper. Each dot represents a particular GCM in CMIP5 for the middle of the century (2025-2075). Vertical lines around each dot represents the 95% confidence interval based on a block bootstrap procedure whereby years of the data are sampled with replacement. The horizontal solid black line and the colored bands correspond to the mean and +/- two standard deviation of each ensemble, respectively. Impact projections for the **A.** middle of the century (2025-2075) and the **B.** end of the century (2050-2100).
Figure S54: Decomposition of climate change impact projections on United States crop yields into moisture and temperature for preferred model based on shorter growing season. Each colored bar represents the CMIP5 ensemble mean contribution to yield impacts for each type of variable. Each dot represents the contribution of the variable to yield impact for a particular GCM. Projections during the A. middle of the century (2025-2075) and the B. end of the century (2050-2100).
Figure S55: Climate change impact projections on United States crop yields based on a state-by-year block bootstrap. Each dot represents a particular GCM in CMIP5 for the middle of the century (2025-2075). Vertical lines around each dot represent the 95% confidence interval based on a block bootstrap procedure whereby years of the data are sampled with replacement. The horizontal solid black line and the colored bands correspond to the mean and +/- two standard deviation of each ensemble, respectively. A. Middle of the century. B. End of the century.
Figure S56: Climate change impact projections on United States crop yields based on a state-by-year block bootstrap. Each dot represents a particular GCM in CMIP5 for the middle of the century (2025-2075). Vertical lines around each dot represent the 95% confidence interval based on a block bootstrap procedure whereby years of the data are sampled with replacement. The horizontal solid black line and the colored bands correspond to the mean and +/- two standard deviation of each ensemble, respectively. **A.** Middle of the century. **B.** End of the century.
Figure S57: Climate change impact projections on United States crop yields based on a county-level block bootstrap. Each dot represents a particular GCM in CMIP5 for the middle of the century (2025-2075). Vertical lines around each dot represent the 95% confidence interval based on a block bootstrap procedure whereby blocks of the data are sampled by county with replacement. The horizontal solid black line and the colored bands correspond to the mean and +/- two standard deviation of each ensemble, respectively. A. Middle of the century. B. End of the century.
### Table S1: Uniform climate scenarios during critical month for the proposed model

| Moisture change (%) | Maize  | Soybeans | Winter wheat | Spring wheat | Cotton | Sorghum |
|---------------------|--------|----------|--------------|--------------|--------|---------|
| -60                 | -22.4  | -22.3    | -20.2        | -43.2        | -10.6  | -9.5    |
| -50                 | -22.7  | -20.2    | -18.1        | -35.6        | -10.1  | -10.4   |
| -40                 | -21.6  | -17.5    | -15.2        | -27.0        | -9.2   | -10.6   |
| -30                 | -18.0  | -13.9    | -11.3        | -18.4        | -7.6   | -9.5    |
| -20                 | -12.0  | -9.3     | -6.9         | -10.5        | -5.3   | -6.8    |
| -10                 | -5.1   | -4.3     | -2.8         | -4.1         | -2.6   | -3.2    |
| 0                   | 0.0    | 0.0      | 0.0          | 0.0          | 0.0    | 0.0     |
| +10                 | 1.3    | 2.5      | 1.0          | 1.6          | 2.0    | 1.3     |
| +20                 | -1.1   | 2.9      | 0.6          | 1.1          | 2.9    | 0.0     |
| +30                 | -5.0   | 1.7      | -0.4         | -0.8         | 2.9    | -3.0    |
| +40                 | -7.6   | 0.1      | -1.4         | -3.0         | 2.3    | -6.5    |
| +50                 | -8.8   | -1.0     | -2.2         | -5.1         | 1.5    | -9.4    |
| +60                 | -9.3   | -1.5     | -2.6         | -6.3         | 0.4    | -11.1   |

| Temperature change (ºC) | Maize  | Soybeans | Winter wheat | Spring wheat | Cotton | Sorghum |
|-------------------------|--------|----------|--------------|--------------|--------|---------|
| -2                      | 2.8    | 1.5      | -1.6         | 2.5          | 11.2   | 5.3     |
| -1                      | 1.9    | 1.1      | -0.7         | 1.7          | 6.0    | 2.9     |
| 0                       | 0.0    | 0.0      | 0.0          | 0.0          | 0.0    | 0.0     |
| +1                      | -3.0   | -1.9     | 0.6          | -2.4         | -6.4   | -3.2    |
| +2                      | -6.8   | -4.5     | 1.0          | -5.6         | -12.8  | -6.6    |
| +3                      | -11.3  | -7.7     | 1.3          | -9.5         | -19.0  | -10.1   |
| +4                      | -16.3  | -11.3    | 1.4          | -13.9        | -24.8  | -13.4   |
| +5                      | -21.6  | -15.3    | 1.4          | -18.8        | -30.1  | -16.7   |
| +6                      | -26.9  | -19.4    | 1.1          | -24.2        | -34.9  | -19.8   |
| +7                      | -32.0  | -23.5    | 0.8          | -30.0        | -39.2  | -22.7   |
| +8                      | -36.8  | -27.5    | 0.3          | -35.9        | -43.0  | -25.3   |
| +9                      | -41.3  | -31.3    | -0.4         | -41.9        | -46.4  | -27.7   |
| +10                     | -45.3  | -34.9    | -1.1         | -47.8        | -49.2  | -29.8   |

Notes: The proposed model accounts for intra-seasonal effects of both soil moisture and temperature throughout the growing season. The identification of the critical month for maize (July), soybeans (August), winter wheat (March), spring wheat (June), cotton (July) and sorghum (July) is discussed in Methods.
Table S2: Ensemble climate change impact projections for proposed model

| Crop  | Scenario | 2025-2075 | 2050-2100 |
|-------|----------|-----------|-----------|
|       |          | RCP 2 | RCP 4.5 | RCP 6.0 | RCP 8.5 | RCP 2 | RCP 4.5 | RCP 6.0 | RCP 8.5 |
|       |          | μ - 2σ | μ + 2σ | μ - 2σ | μ + 2σ | μ - 2σ | μ + 2σ | μ - 2σ | μ + 2σ | min | μ | μ + 2σ | max | N |
|-------|----------|--------|--------|--------|--------|--------|--------|--------|--------|------|-----|--------|------|---|
| Maize |          | 2.6    | -20.5  | -24.2  | -14.8  | -5.5   | -6.3   | 15     | -24.4  | -28.4 | -15.9 | -3.4   | -4.2 | 15 |
|       |          | 4.5    | -32.9  | -34.5  | -20.2  | -5.9   | -7.9   | 17     | -41.4  | -46.0 | -26.2 | -6.4   | -7.7 | 17 |
|       |          | 6.0    | -23.2  | -28.3  | -17.7  | -7.2   | -7.7   | 9      | -36.3  | -44.3 | -28.5 | -12.6  | -11.8 | 9  |
|       |          | 8.5    | -39.7  | -46.3  | -29.4  | -12.5  | -11.6  | 19     | -59.0  | -73.1 | -48.1 | -23.1  | -21.9 | 17 |
| Soybeans |      | 2.6    | -20.7  | -20.7  | -11.2  | -1.8   | -3.4   | 15     | -20.1  | -23.7 | -12.1 | -0.5  | -1.0  | 15 |
|       |          | 4.5    | -29.0  | -28.6  | -15.3  | -2.1   | -4.8   | 17     | -39.5  | -40.1 | -20.4 | -0.7  | -4.6  | 17 |
|       |          | 6.0    | -25.0  | -27.1  | -14.4  | -1.7   | -4.9   | 9      | -38.0  | -42.3 | -23.5 | -4.6  | -8.0  | 9  |
|       |          | 8.5    | -44.6  | -42.2  | -23.8  | -5.3   | -7.7   | 19     | -57.2  | -64.0 | -39.1 | -14.2 | -15.6 | 17 |
| Winter |         | 2.6    | -11.3  | -12.7  | -7.7   | -2.7   | -2.7   | 15     | -10.1  | -11.9 | -7.6  | -3.3  | -3.0  | 15 |
| Wheat  |         | 4.5    | -14.2  | -17.5  | -10.2  | -3.0   | -3.9   | 17     | -17.0  | -21.2 | -12.5 | -3.8  | -3.4  | 17 |
|       |          | 6.0    | -11.4  | -12.3  | -7.7   | -3.1   | -3.4   | 9      | -16.6  | -18.5 | -11.7 | -4.8  | -5.2  | 9  |
|       |          | 8.5    | -18.6  | -20.7  | -13.0  | -5.3   | -5.6   | 19     | -26.8  | -31.6 | -20.1 | -8.6  | -10.5 | 17 |
| Spring |         | 2.6    | -26.9  | -32.6  | -18.3  | -4.0   | 1.2    | 15     | -29.1  | -35.2 | -19.2 | -3.1  | 0.4   | 15 |
| Wheat  |         | 4.5    | -32.8  | -40.5  | -23.0  | -5.5   | -0.1   | 17     | -39.9  | -46.9 | -28.6 | -10.3 | -4.0  | 17 |
|       |          | 6.0    | -27.9  | -35.3  | -20.7  | -6.1   | -3.9   | 9      | -40.7  | -48.8 | -30.4 | -11.9 | -9.1  | 9  |
|       |          | 8.5    | -40.5  | -46.6  | -28.9  | -11.3  | -9.9   | 19     | -56.0  | -67.4 | -44.3 | -21.2 | -21.4 | 17 |
| Cotton |         | 2.6    | -17.0  | -19.2  | -13.1  | -6.9   | -7.5   | 15     | -18.9  | -19.9 | -13.2 | -6.4  | -6.9  | 15 |
|       |          | 4.5    | -22.1  | -23.7  | -14.7  | -5.8   | -7.1   | 17     | -23.3  | -27.1 | -17.5 | -7.9  | -7.1  | 17 |
|       |          | 6.0    | -22.8  | -25.4  | -16.1  | -6.8   | -8.2   | 9      | -30.0  | -32.1 | -21.3 | -10.4 | -13.6 | 9  |
|       |          | 8.5    | -33.7  | -31.6  | -21.6  | -11.7  | -12.5  | 19     | -37.3  | -39.9 | -30.0 | -20.1 | -19.2 | 17 |
| Sorghum |       | 2.6    | -21.7  | -23.8  | -14.4  | -5.1   | -6.7   | 15     | -22.1  | -24.6 | -14.6 | -4.7  | -5.9  | 15 |
|       |          | 4.5    | -30.7  | -34.3  | -19.4  | -4.6   | -7.7   | 17     | -35.2  | -40.0 | -23.7 | -7.3  | -8.4  | 17 |
|       |          | 6.0    | -23.8  | -29.2  | -18.3  | -7.3   | -7.2   | 9      | -33.8  | -39.7 | -26.0 | -12.3 | -11.6 | 9  |
|       |          | 8.5    | -36.6  | -39.5  | -26.0  | -12.5  | -12.3  | 19     | -49.2  | -58.2 | -39.7 | -21.2 | -20.1 | 17 |

Notes: The proposed model accounts for intra-seasonal variations in soil moisture and temperature effects throughout the growing season.
Table S3: Ensemble climate change impact projections for traditional model

| Crop    | Scenario | 2025-2075 | | 2050-2100 | |
|---------|----------|-----------|---|-----------|---|
|         |          | min $\mu - 2\sigma$ | $\mu$ | $\mu + 2\sigma$ | max | N | min $\mu - 2\sigma$ | $\mu$ | $\mu + 2\sigma$ | max | N |
| Maize   | 2.6      | -23.2     | -23.4 | -14.2 | -5.1 | -5.0 | 15 | -27.0 | -27.9 | -15.3 | -2.7 | 3.2 | 15 |
|         | 4.5      | -30.5     | -30.5 | -18.4 | -6.4 | -6.0 | 17 | -41.5 | -43.6 | -25.1 | -6.6 | -6.6 | 17 |
|         | 6.0      | -25.5     | -27.8 | -16.5 | -5.1 | -6.7 | 9  | -39.9 | -46.0 | -27.9 | -9.8 | -11.3 | 9  |
|         | 8.5      | -37.5     | -44.5 | -28.2 | -12.0 | -11.9 | 19 | -61.5 | -72.8 | -47.8 | -22.8 | -23.7 | 17 |
| Soybeans| 2.6      | -15.8     | -15.9 | -9.7  | -3.5 | -4.3 | 15 | -18.9 | -19.3 | -10.6 | -1.9 | -2.7 | 15 |
|         | 4.5      | -21.2     | -20.8 | -13   | -5.1 | -4.9 | 17 | -29.7 | -31.0 | -18.1 | -5.1 | -5.2 | 17 |
|         | 6.0      | -17.2     | -20.7 | -11.8 | -2.9 | -5.1 | 9  | -28.7 | -34.8 | -20.5 | -6.2 | -8.6 | 9  |
|         | 8.5      | -30.2     | -34.0 | -21   | -7.9 | -7.9 | 19 | -50.3 | -59.2 | -37.5 | -15.8 | -16.7 | 17 |
| Winter  | 2.6      | -9.6      | -10.8 | -7.1  | -3.5 | -3.9 | 15 | -11.1 | -11.8 | -7.3  | -2.9 | -3.1 | 15 |
| Wheat   | 4.5      | -11.3     | -13.7 | -8.9  | -4.0 | -3.5 | 17 | -14.5 | -17.2 | -11.2 | -5.2 | -4.7 | 17 |
|         | 6.0      | -9.3      | -10.9 | -8.2  | -5.4 | -4.9 | 9  | -14.4 | -17.0 | -12.4 | -7.9 | -7.6 | 9  |
|         | 8.5      | -14.3     | -17.3 | -11.9 | -6.6 | -6.1 | 19 | -23.6 | -28.1 | -19.6 | -11.0 | -10.9 | 17 |
| Spring  | 2.6      | -22.1     | -25.7 | -14.7 | -3.7 | 0.8  | 15 | -24.5 | -29.6 | -15.7 | -1.7 | 0.9  | 15 |
| Wheat   | 4.5      | -26.9     | -33.8 | -19.2 | -4.6 | -0.3 | 17 | -32.9 | -40.8 | -24.6 | -8.4 | -4.1 | 17 |
|         | 6.0      | -22.8     | -28.9 | -16.6 | -4.3 | -2.3 | 9  | -36.7 | -42.8 | -26.5 | -10.3 | -7.7 | 9  |
|         | 8.5      | -35.1     | -40.3 | -25.7 | -11.2 | -9.5 | 19 | -51.6 | -62.0 | -41.4 | -20.8 | -20.8 | 17 |
| Cotton  | 2.6      | -31.5     | -30.0 | -21.4 | -12.8 | -13.6 | 15 | -34.3 | -32.5 | -22.2 | -11.8 | -12.7 | 15 |
|         | 4.5      | -31.3     | -35.4 | -25.6 | -15.9 | -13.5 | 17 | -38.6 | -42.7 | -30.9 | -19.0 | -15.4 | 17 |
|         | 6.0      | -32.3     | -34.7 | -25.2 | -15.7 | -18.0 | 9  | -44.5 | -47.5 | -34.8 | -22.0 | -26.0 | 9  |
|         | 8.5      | -43.3     | -46.7 | -34.1 | -21.5 | -20.6 | 19 | -58.6 | -64.1 | -48.6 | -33.1 | -33.3 | 17 |
| Sorghum | 2.6      | -22.9     | -23.0 | -15.7 | -8.3  | -9.0 | 15 | -26.3 | -25.3 | -16.2 | -7.2 | -7.4 | 15 |
|         | 4.5      | -26.6     | -28.5 | -19.6 | -10.6 | -11.0 | 17 | -33.2 | -35.5 | -24.4 | -13.2 | -12.7 | 17 |
|         | 6.0      | -24.2     | -27.0 | -18.6 | -10.2 | -11.0 | 9  | -35.3 | -38.9 | -27.0 | -15.1 | -16.6 | 9  |
|         | 8.5      | -34.1     | -39.0 | -26.9 | -14.9 | -14.2 | 19 | -50.8 | -59.3 | -41.9 | -24.6 | -24.7 | 17 |

Notes: The proposed model accounts for intra-seasonal variations in soil moisture and temperature effects throughout the growing season.
| Crop       | RCP | \( \mu_1 \) | \( \mu_2 \) | \( \mu_2 - \mu_1 \) | 5% | 10% | N | 5% | 10% | N |
|------------|-----|-------------|-------------|---------------------|----|-----|---|----|-----|---|
| Maize      | 2.6 | -14.2       | -14.8       | -0.6                | 0  | 0   | 15| -15.3| -15.9| -0.6| 0  | 0   | 15|
|            | 4.5 | -18.4       | -20.2       | -1.8                | 0  | 0   | 17| -25.1| -26.2| -1.1| 0  | 0   | 17|
|            | 6.0 | -16.5       | -17.7       | -1.2                | 0  | 0   | 9 | -27.9| -28.5| -0.5| 0  | 0   | 9  |
|            | 8.5 | -28.2       | -29.4       | -1.2                | 0  | 0   | 19| -47.8| -48.1| -0.3| 0  | 0   | 17|
| Soybeans   | 2.6 | -9.7        | -11.2       | -1.5                | 1  | 1   | 15| -10.6| -12.1| -1.5| 1  | 1   | 15|
|            | 4.5 | -13.0       | -15.3       | -2.4                | 3  | 3   | 17| -18.1| -20.4| -2.3| 2  | 2   | 17|
|            | 6.0 | -11.8       | -14.4       | -2.5                | 1  | 1   | 9 | -20.5| -23.5| -3.0| 1  | 1   | 9  |
|            | 8.5 | -21.0       | -23.8       | -2.8                | 4  | 4   | 19| -37.5| -39.1| -1.6| 0  | 2   | 17|
| Winter     | 2.6 | -7.1        | -7.7        | -0.5                | 0  | 0   | 15| -7.3 | -7.6 | -0.3| 0  | 0   | 15|
| Wheat      | 4.5 | -8.9        | -10.2       | -1.4                | 0  | 0   | 17| -11.2| -12.5| -1.3| 0  | 0   | 17|
|            | 6.0 | -8.2        | -7.7        | 0.5                 | 0  | 0   | 9 | -12.4| -11.7| 0.7 | 0  | 0   | 9  |
|            | 8.5 | -11.9       | -13.0       | -1.1                | 0  | 0   | 19| -19.6| -20.1| -0.5| 0  | 0   | 17|
| Spring     | 2.6 | -14.7       | -18.3       | -3.6                | 0  | 0   | 15| -15.7| -19.2| -3.5| 0  | 0   | 15|
| Wheat      | 4.5 | -19.2       | -23.0       | -3.8                | 0  | 0   | 17| -24.6| -28.6| -4.0| 0  | 0   | 17|
|            | 6.0 | -16.6       | -20.7       | -4.1                | 0  | 0   | 9 | -26.5| -30.4| -3.8| 0  | 0   | 9  |
|            | 8.5 | -25.7       | -28.9       | -3.2                | 0  | 0   | 19| -41.4| -44.3| -2.9| 0  | 0   | 17|
| Cotton     | 2.6 | -21.4       | -13.1       | 8.4                 | 0  | 4   | 15| -22.2| -13.2| 9.0 | 2  | 5   | 15|
|            | 4.5 | -25.6       | -14.7       | 10.9                | 3  | 8   | 17| -30.9| -17.5| 13.4| 4  | 10  | 17|
|            | 6.0 | -25.2       | -16.1       | 9.1                 | 0  | 4   | 9 | -34.8| -21.3| 13.5| 2  | 4   | 9  |
|            | 8.5 | -34.1       | -21.6       | 12.5                | 2  | 5   | 19| -48.6| -30.0| 18.7| 5  | 15  | 17|
| Sorghum    | 2.6 | -15.7       | -14.4       | 1.2                 | 0  | 0   | 15| -16.2| -14.6| 1.6 | 0  | 0   | 15|
|            | 4.5 | -19.6       | -19.4       | 0.1                 | 0  | 0   | 17| -24.4| -23.7| 0.7 | 0  | 0   | 17|
|            | 6.0 | -18.6       | -18.3       | 0.3                 | 0  | 0   | 9 | -27.0| -26.0| 0.9 | 0  | 0   | 9  |
|            | 8.5 | -26.9       | -26.0       | 1.0                 | 0  | 0   | 19| -41.9| -39.7| 2.2 | 0  | 0   | 17|

Notes: \( \mu_1 \) and \( \mu_2 \) refer to the GCM ensemble-mean climate change impact for the traditional model based on season-long precipitation and temperature effects, and the proposed model based on intra-seasonal effects of soil moisture and temperature, respectively. “Signif” refers to the number of GCMs in the ensemble for which the impact differences are statistically significant at the 5 and 10% levels. “N” refers to the total number of GCMs in the ensemble for a given scenario (RCP) and projection period.
Table S5: Mean climate change impacts on crop yields (%) for proposed model (1) and alternative model based on intra-seasonal precipitation and temperature effects (2)

| Crop    | RCP | \( \mu_1 \) | \( \mu_2 \) | \( \mu_2 - \mu_1 \) | 5%  | 10%  | N signif. | 2050-2100 | \( \mu_1 \) | \( \mu_2 \) | \( \mu_2 - \mu_1 \) | 5%  | 10%  | N signif. |
|---------|-----|-------------|-------------|----------------------|-----|-----|---------|-----------|-------------|-------------|----------------------|-----|-----|---------|
| Maize   | 2.6 | -14.8      | -14.0       | 0.9                  | 0   | 0   | 15      | 4.5       | -20.2       | -18.6       | 1.6                  | 0   | 0   | 17      |
|         | 6.0 | -17.7      | -16.8       | 0.9                  | 0   | 0   | 9       | 8.5       | -29.4       | -27.4       | 2.0                  | 0   | 0   | 17      |
| Soybeans| 2.6 | -11.2      | -10.5       | 0.7                  | 0   | 0   | 15      | 4.5       | -15.3       | -14.2       | 1.1                  | 0   | 0   | 17      |
|         | 6.0 | -14.4      | -13.3       | 1.0                  | 1   | 1   | 9       | 8.5       | -23.8       | -22.4       | 1.4                  | 0   | 1   | 17      |
| Winter  | 2.6 | -7.7       | -6.4        | 1.3                  | 0   | 0   | 15      | 4.5       | -10.2       | -7.8        | 2.5                  | 0   | 0   | 17      |
| Wheat   | 6.0 | -7.7       | -6.9        | 0.9                  | 0   | 0   | 9       | 8.5       | -13.0       | -10.5       | 2.5                  | 0   | 0   | 17      |
| Spring  | 2.6 | -18.3      | -17.4       | 0.9                  | 0   | 0   | 15      | 4.5       | -23.0       | -21.8       | 1.2                  | 0   | 0   | 17      |
| Wheat   | 6.0 | -20.7      | -20.6       | 0.1                  | 0   | 0   | 9       | 8.5       | -28.9       | -28.2       | 0.8                  | 0   | 0   | 17      |
| Cotton  | 2.6 | -13.1      | -16.6       | -3.6                 | 0   | 0   | 15      | 4.5       | -14.7       | -19.4       | -4.3                 | 0   | 0   | 17      |
|         | 6.0 | -16.1      | -19.9       | -3.8                 | 0   | 0   | 9       | 8.5       | -21.6       | -27.3       | -5.7                 | 0   | 0   | 17      |
| Sorghum | 2.6 | -14.4      | -13.4       | 1.0                  | 1   | 2   | 15      | 4.5       | -19.4       | -17.2       | 2.2                  | 4   | 5   | 17      |
|         | 6.0 | -18.3      | -15.9       | 2.4                  | 2   | 3   | 9       | 8.5       | -26.0       | -24.2       | 1.8                  | 1   | 2   | 19      |

Notes: \( \mu_1 \) and \( \mu_2 \) refer to the GCM ensemble mean climate change impact for the proposed model with intra-seasonal effects of soil moisture and temperature and an alternative model based on intra-seasonal effects of precipitation and temperature, respectively. "Signif" refers to the number of GCMs in the ensemble for which the impact differences are statistically significant at the 5 and 10% levels. "N" refers to the total number of GCMs in the ensemble for a given scenario (RCP) and projection period.
Table S6: Mean climate change impacts on crop yields (%) for proposed model estimated based on 1981-1999 (1) and 2000-2017 (2) data

| Crop   | RCP | $\mu_1$ | $\mu_2$ | $\mu_2 - \mu_1$ | 5% | 10% | N signif. | 5% | 10% | N | Signif. |
|--------|-----|---------|---------|-----------------|----|-----|---------|----|-----|---|---------|
| Maize  | 2.6 | -15.6   | -17.2   | -1.6            | 0  | 0   | 15      | -16.8 | -18.1 | -1.3 | 0  | 0   | 15 |
|        | 4.5 | -21.2   | -22.4   | -1.2            | 0  | 0   | 17      | -27.8  | -28.2 | -0.4 | 0  | 0   | 17 |
|        | 6.0 | -18.6   | -19.9   | -1.3            | 0  | 0   | 9       | -30.6  | -30.0 | 0.6  | 0  | 0   | 9 |
|        | 8.5 | -31.6   | -30.8   | 0.7             | 0  | 0   | 19      | -51.9  | -48.0 | 3.9  | 0  | 0   | 17 |
| Soybeans| 2.6 | -11.1   | -9.5    | 1.6             | 0  | 0   | 15      | -12.1  | -10.3 | 1.8  | 0  | 0   | 15 |
|        | 4.5 | -15.2   | -13.5   | 1.8             | 0  | 0   | 17      | -20.4  | -18.5 | 1.9  | 0  | 0   | 17 |
|        | 6.0 | -14.1   | -12.6   | 1.5             | 0  | 0   | 9       | -23.2  | -21.7 | 1.5  | 0  | 0   | 9 |
|        | 8.5 | -23.7   | -22.2   | 1.6             | 0  | 0   | 19      | -39.3  | -38.1 | 1.2  | 0  | 0   | 17 |
| Winter | 2.6 | -6.7    | -8.5    | -1.8            | 0  | 0   | 15      | -6.7   | -8.5   | -1.8 | 0  | 0   | 15 |
| Wheat  | 4.5 | -8.9    | -11.3   | -2.3            | 0  | 0   | 17      | -11.1  | -13.5 | -2.4 | 0  | 0   | 17 |
|        | 6.0 | -6.5    | -8.5    | -2.0            | 0  | 0   | 9       | -10.6  | -12.1 | -1.5 | 0  | 0   | 9 |
|        | 8.5 | -11.7   | -14.0   | -2.3            | 0  | 0   | 19      | -18.7  | -20.4 | -1.7 | 0  | 0   | 17 |
| Spring | 2.6 | -19.8   | -16.1   | 3.7             | 0  | 0   | 15      | -20.5  | -17.0 | 3.5  | 0  | 0   | 15 |
| Wheat  | 4.5 | -24.6   | -20.3   | 4.3             | 0  | 0   | 17      | -30.3  | -25.4 | 5.0  | 0  | 0   | 17 |
|        | 6.0 | -22.1   | -18.2   | 3.9             | 0  | 0   | 9       | -31.7  | -27.5 | 4.1  | 0  | 0   | 9 |
|        | 8.5 | -30.5   | -25.9   | 4.6             | 0  | 0   | 19      | -45.4  | -40.4 | 5.0  | 0  | 0   | 17 |
| Cotton | 2.6 | -17.5   | -14.3   | 3.1             | 0  | 0   | 15      | -17.8  | -14.4 | 3.4  | 0  | 0   | 15 |
|        | 4.5 | -20.0   | -16.5   | 3.5             | 0  | 0   | 17      | -24.2  | -19.2 | 5.0  | 0  | 0   | 17 |
|        | 6.0 | -20.8   | -18.1   | 2.7             | 0  | 0   | 9       | -28.5  | -23.4 | 5.1  | 0  | 0   | 9 |
|        | 8.5 | -29.0   | -22.8   | 6.3             | 0  | 0   | 19      | -42.1  | -30.9 | 11.2 | 0  | 0   | 17 |
| Sorghum| 2.6 | -13.6   | -20.8   | -7.2            | 3  | 3   | 15      | -13.9  | -20.8 | -6.9 | 2  | 2   | 15 |
|        | 4.5 | -18.2   | -26.7   | -8.5            | 3  | 4   | 17      | -22.5  | -30.7 | -8.2 | 3  | 3   | 17 |
|        | 6.0 | -17.1   | -25.6   | -8.5            | 3  | 3   | 9       | -25.0  | -32.4 | -7.4 | 3  | 3   | 9 |
|        | 8.5 | -24.8   | -32.2   | -7.3            | 3  | 3   | 19      | -39.1  | -43.0 | -3.9 | 0  | 2   | 17 |

Notes: $\mu_1$ and $\mu_2$ refer to the GCM ensemble mean climate change impact for the proposed model estimated over two different periods, 1981-1999 and 2000-2017, respectively. "Signif" refers to the number of GCMs in the ensemble for which the impact differences are statistically significant at the 5 and 10% levels. "N" refers to the total number of GCMs in the ensemble for a given scenario (RCP) and projection period. The comparison is based on a quasi-balanced sample (observations with over 75% of years in the data) to avoid comparing a very different set of counties across the two time periods.
Table S7: Mean climate change impacts on crop yields (%) for proposed model for northern (1) and southern (2) subsamples

| Crop      | RCP | \( \mu_1 \) | \( \mu_2 \) | \( \mu_2 - \mu_1 \) | N signif. 5% | N signif. 10% | N | \( \mu_1 \) | \( \mu_2 \) | \( \mu_2 - \mu_1 \) | Signif. 5% | Signif. 10% | N |
|-----------|-----|-------------|-------------|----------------------|-------------|---------------|---|-------------|-------------|----------------------|------------|-------------|---|
| Maize     | 2.6 | -16.4       | -16.1       | 0.2                  | 0           | 0             | 15 | -17.5       | -17.2       | 0.2                  | 0          | 0            | 15 |
|           | 4.5 | -22.1       | -21.6       | 0.5                  | 0           | 0             | 17 | -28.9       | -27.6       | 1.3                  | 0          | 0            | 17 |
|           | 6.0 | -19.6       | -19.1       | 0.5                  | 0           | 0             | 9  | -31.8       | -29.6       | 2.3                  | 0          | 0            | 9  |
|           | 8.5 | -32.9       | -30.5       | 2.4                  | 0           | 0             | 19 | -53.0       | -48.5       | 4.5                  | 0          | 2            | 17 |
| Soybeans  | 2.6 | -9.4        | -16         | -6.6                 | 3           | 6             | 15 | -10.1       | -17.0       | -6.9                 | 4          | 6            | 15 |
|           | 4.5 | -13.3       | -20.6       | -7.3                 | 4           | 8             | 17 | -18.0       | -26.0       | -8.0                 | 0          | 6            | 17 |
|           | 6.0 | -12.3       | -19.4       | -7.1                 | 0           | 5             | 9  | -20.9       | -29.2       | -8.3                 | 0          | 2            | 9  |
|           | 8.5 | -21.6       | -29.2       | -7.6                 | 0           | 5             | 19 | -37.0       | -43.9       | -7.0                 | 0          | 0            | 17 |
| Winter    | 2.6 | -7.5        | -6.9        | 0.5                  | 0           | 0             | 15 | -7.2        | -6.9        | 0.3                  | 0          | 0            | 15 |
| Wheat     | 4.5 | -10.7       | -9.0        | 1.8                  | 0           | 0             | 17 | -12.9       | -11.1       | 1.8                  | 0          | 0            | 17 |
|           | 6.0 | -7.3        | -6.9        | 0.3                  | 0           | 0             | 9  | -10.8       | -10.9       | -0.2                 | 0          | 0            | 9  |
|           | 8.5 | -13.7       | -11.4       | 2.2                  | 0           | 0             | 19 | -21.7       | -18         | 3.7                  | 0          | 0            | 17 |
| Spring    | 2.6 | -18.5       | -18.5       | 0.0                  | 0           | 0             | 15 | -19.4       | -19.4       | 0.0                  | 0          | 0            | 15 |
| Wheat     | 4.5 | -23.3       | -23.0       | 0.3                  | 0           | 0             | 17 | -29.0       | -28.6       | 0.4                  | 0          | 0            | 17 |
|           | 6.0 | -20.9       | -21.1       | -0.2                 | 0           | 0             | 9  | -30.6       | -30.7       | -0.1                 | 0          | 0            | 9  |
|           | 8.5 | -29.2       | -29.2       | 0.0                  | 0           | 0             | 19 | -44.5       | -44.2       | 0.3                  | 0          | 0            | 17 |
| Cotton    | 2.6 | -11.4       | -14         | -2.6                 | 0           | 0             | 15 | -11.4       | -14.2       | -2.8                 | 0          | 0            | 15 |
|           | 4.5 | -12.7       | -16         | -3.3                 | 0           | 0             | 17 | -15.0       | -18.8       | -3.8                 | 0          | 0            | 17 |
|           | 6.0 | -14.5       | -17.2       | -2.7                 | 0           | 0             | 9  | -19.5       | -22.2       | -2.7                 | 0          | 0            | 9  |
|           | 8.5 | -19.8       | -22.5       | -2.7                 | 0           | 0             | 19 | -28.3       | -30.2       | -1.8                 | 0          | 0            | 17 |
| Sorghum   | 2.6 | -16.4       | -15.2       | 1.3                  | 3           | 3             | 15 | -16.5       | -15.5       | 1.0                  | 1          | 2            | 15 |
|           | 4.5 | -22.4       | -19.7       | 2.6                  | 3           | 4             | 17 | -26.9       | -24.1       | 2.9                  | 3          | 3            | 17 |
|           | 6.0 | -21.1       | -18.4       | 2.7                  | 2           | 2             | 9  | -29.6       | -26.3       | 3.3                  | 1          | 3            | 9  |
|           | 8.5 | -29.9       | -25.9       | 3.9                  | 3           | 4             | 19 | -44.9       | -39.2       | 5.7                  | 3          | 4            | 17 |

Notes: \( \mu_1 \) and \( \mu_2 \) refer to the GCM ensemble mean climate change impact for the proposed model for the northern and southern subsamples, respectively. “Signif” refers to the number of GCMs in the ensemble for which the impact differences are statistically significant at the 5 and 10% levels. “N” refers to the total number of GCMs in the ensemble for a given scenario (RCP) and projection period.
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