# US Major Crops' Uncertain Climate Change Risks and Greenhouse Gas Mitigation Benefits

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# US Major Crops' Uncertain Climate Change Risks and Greenhouse Gas Mitigation Benefits

Ian Sue Wing,*† Erwan Monier,‡ Ari Stern,§ and Anupriya Mundra¶

**Abstract**

*We estimate the costs of climate change to US agriculture, and associated potential benefits of abating greenhouse gas emissions. Five major crops yield responses to climatic variation are modeled empirically, and the results combined with climate projections for a no-policy, high-warming future, as well as moderate and stringent mitigation scenarios. Unabated warming reduces yields of wheat and soybeans by 2050, and cotton by 2100, but moderate warming increases yields of all crops except wheat. Yield changes are monetized using the results of economic simulations within an integrated climate-economy modeling framework. The economic effects of uncontrolled warming on major crops are slightly positive—annual benefits < \$4B. These are amplified by emission reductions, but subject to diminishing returns—by 2100 reaching \$17B under moderate mitigation, but only \$7B with stringent mitigation. Costs and benefits are sensitive to irreducible uncertainty about the fertilization effects of elevated atmospheric carbon dioxide, without which unabated warming incurs net costs of up to \$18B, generating benefits to moderate (stringent) mitigation as large as \$26B (\$20B).*

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## 1. INTRODUCTION

What are the costs and benefits to US agriculture of mitigating greenhouse gas (GHG) emissions? Agriculture has significant climate change exposure, but despite being a sector that has long been studied (e.g., Mendelsohn *et al.*, 1994), projections of future crops impacts and associated costs of damage remain too uncertain to provide a definitive answer. The issue is highlighted by disagreements over the responses of US agricultural yields and profits inferred from historical observations, and their implications for the sign and magnitude of future climate impacts.

The empirical climate economics literature provides ample evidence that yields of major US crops are adversely affected by exposure to cumulative growing season degree day extremes

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(Schlenker *et al.*, 2006; Fisher *et al.*, 2012) and temperatures above a 86°F (30°C) threshold (Schlenker and Roberts, 2009; Ortiz-Bobea and Just, 2012). But the economic consequences are contested. The robustness of accumulated heats adverse effects on farm profits (Schlenker *et al.*, 2006; Fisher *et al.*, 2012) has been questioned in light of the potentially confounding influence of spatially and temporally varying *non*-climatic factors (Deschênes and Greenstone, 2007, 2012). When combined with earth system model (ESM) simulations of future climate, the latter responses suggest that climatic changes experienced by 2100 would have only small impacts on today's agricultural system (annual losses of $4B to $16B in 2002 USD).

Additional uncertainty abounds in the future trajectory of production, and meteorological exposure, of US agriculture—even for a given warming scenario. Despite improved understanding of climate change feedbacks on land use (Hurtt *et al.*, 2011), the future geographic distribution and output expansion of US field crops remain indeterminate. With fixed cropping patterns and warming trajectories, assessment using meteorological exposures from an ensemble of ESMs can increase the range of projected impacts and the magnitude of "worst-case" losses (Deschênes and Greenstone, 2012, and especially Burke *et al.*, 2015). Addressing the latter uncertainty, the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) uses global gridded crop models (GGCMs) forced by ESM ensemble projections to quantify the range of crop shocks to crop yields (Rosenzweig *et al.*, 2014), which are in turn employed as input forcings to integrated assessment models (IAMs) that simulate concomitant crop production, price and economic welfare impacts (Nelson *et al.*, 2014).

The dollar value of damages depends critically on the uncertain state of the economy in the future decades when climate change affects crop yields. However, the ISI-MIP impact modeling protocol's baseline socio-economic, technological and GHG mitigation trajectories are not synchronized with the assumptions used by the IAMs that simulate the representative concentration pathway (RCP) scenarios forcing ESM projections. The key omission is the relative price effects of the GHG mitigation measures that are necessary to realize low-radiative forcing futures. Cost-benefit analysis requires a modeling framework that can simulate the economic effects of mitigation, the climatic consequences of the resulting emissions, the concomitant biophysical impacts *and their effects on the perturbed economy*. A further limitation is that the resulting economic impacts understate the potential benefits of GHG mitigation by including adaptation that arises out of IAMs price-driven substitution responses—among the inputs to crop production and the outputs of agricultural sectors, and between other goods and agriculture, and domestic and imported varieties of each commodity (Nelson *et al.*, 2014)—whose cost-reducing effects are difficult to monetize.[1]

This paper draws upon and extends aforementioned approaches to estimate the costs of climate change in US agriculture, and the potential benefits of GHG mitigation, in a manner that excludes adaptation and is both economically and climatically consistent. We first econometrically model the long-run yield response of five major crops (corn, soybeans, wheat, cotton, sorghum) to climatic variation, using data on weather, output and harvested area for ∼3000 counties in the coterminous US over the period 1948–2010. We then combine the resulting yield responses

[1] These are passive adaptations mediated by relative price changes (see Sue Wing and Fisher-Vanden, 2013).

with ESM simulations of climate change scenarios prepared for the US Environmental Protection Agency's Climate Change Impacts and Risk Analysis (CIRA) project (Waldhoff *et al.*, 2015) to estimate yield changes under a no-policy high-warming future as well as two lower-warming emissions mitigation scenarios. We use the resulting yield shocks in conjunction with the output of the computable general equilibrium (CGE) economic model used for the CIRA emissions scenarios (MIT EPPA, see Paltsev *et al.*, 2015) to calculate aggregate economic costs in terms of future revenue changes in each scenario. Cost differences between the no-policy and mitigation scenarios indicate the benefits of reducing GHG emissions.

We find that unmitigated climate change has substantial adverse effects on yields of soybeans and wheat wheat by 2050 and cotton by 2100, but compensating beneficial impacts on corn and sorghum yields. Climatic shocks exhibit substantial geographic variation: regions with cooler average climates show yield increases, while those with warmer average climates show yield reductions. Over time, impacts became increasingly severe at lower latitudes. If climatic changes projected by 2100 under the reference warming scenario were to occur today, annual major crop revenues would be largely unaffected; however, once the agriculture sector's projected future expansion is taken into account, the upshot is an annual net benefit of US (2010) $3B by 2050, which falls to $1.3B by 2100. Forgoing less vigorous climate change is nonetheless costly. Both mitigation policy scenarios have net beneficial effects—up to $1.2B by 2050 and $2B by 2100 if climate change were to impact today's agricultural system, or $3.3B by 2050 and almost $17B by 2100 with the price and output level that are projected in the future. However, these results are sensitive to the specification of the carbon dioxide ($CO_2$) fertilization effect (CFE). The influence of CFE on yields is thought to be positive, but this is subject to considerable uncertainty. Omitting the CFE flips the sign of our impact estimates, giving rise to net agriculture sector costs as high as $18B, with attendant amplification of mitigation benefits.

The rest of the paper is organized as follows. Section 2 summarizes our methodology for empirically modeling climate-yield relationships and coupling these with ESM simulations. Section 3 presents the resulting yield responses to climate change, changes in crop output at the county and regional levels, and monetized damages. In Section 4 we offer a summary of our findings and discussion of their caveats.

## 2. METHODS

### 2.1 Empirical Analysis: Using Historical Observations to Infer Climate Impact on Yields

Following the recent climate-economics literature (Schlenker *et al.*, 2006; Schlenker and Roberts, 2009; Deschênes and Greenstone, 2007, 2012; Lobell and Burke, 2010; Ortiz-Bobea and Just, 2012; Burke and Emerick, 2015) we quantify the potentially nonlinear influence of climate on yields using semi-parametric cross section-time series regressions. Previous studies exploit the historical co-variation between yields and weather shocks to infer the effects of future climate. Motivated by Burke and Emerick (2015)'s finding that long-run adaptations are limited in their ability to alleviate the short-run impacts of extreme heat, we extend their approach using a dynamic modeling framework that statistically distinguishes between the effects of short-run (weather) and long-run (climate) shocks. Since farmers' planting, management and harvesting decisions are based on land quality and expectations of weather, yields and meteorological variables share a long-run equilibrium relationship. In any given year, weather shocks cause yields to diverge from their expected long-run values, prompting farmers to revise their long-run expectations, and make management decisions that can have persistent effects.[2]

To statistically identify the former equilibrium and latter disequilibrium responses we employ an error-correction model (ECM).[3] Our data are an unbalanced panel of $c$ counties over $t$ years, recording yields, $Y$ (calculated as the ratio of production, $Q$, to harvested area, $H$), as well as three-hourly observations of growing season temperature, precipitation and soil moisture, indexed by $v = \{T, P, S\}$ respectively. Interannual variation in log annual yield ($y$) is modeled as a function of a vector of county specific effects ($\mu$, which capture the influence of unobserved time-invariant local characteristics such as topography and soils), a vector of climatic covariates (within each annual growing season, the cumulative exposure over $g$ crop growth stages to $j$ temperature intervals, $\xi^T_{j,g}$, $k$ precipitation intervals, $\xi^P_{k,g}$, and $l$ soil moisture intervals, $\xi^S_{l,g}$), and a vector of time-varying county-level statistical controls ($\boldsymbol{X}$).

Our model, which is derived and explained in the Appendices, is written:

$$\begin{aligned}\Delta y_{c,t} = y_{c,t} - y_{c,t-1} = \log\left(\frac{Q_{c,t}}{H_{c,t}}\right) - \log\left(\frac{Q_{c,t-1}}{H_{c,t-1}}\right) \qquad (1)\\
= \mu_c + \sum_g \left\{ \sum_j \beta^T_{j,g}\Delta\xi^T_{j,g,c,t} + \sum_k \beta^P_{k,g}\Delta\xi^P_{k,g,c,t} + \sum_l \beta^S_{l,g}\Delta\xi^S_{l,g,c,t} \right\} + \Delta\boldsymbol{X}_{c,t}\boldsymbol{\gamma}\\
+\theta\left[ y_{c,t-1} - \sum_g \left\{ \sum_j \eta^T_{j,g}\xi^T_{j,g,c,t-1} + \sum_k \eta^P_{k,g}\xi^P_{k,g,c,t-1} + \sum_l \eta^S_{l,g}\xi^S_{l,g,c,t-1} \right\} + \boldsymbol{X}_{c,t-1}\boldsymbol{\lambda} \right] + \varepsilon_{c,t}\end{aligned}$$

and is estimated via ordinary least squares for five crops (corn, soybeans, wheat, cotton, sorghum), indexed by $i$. Interannual difference terms (prefixed by $\Delta$) model the yield impacts of transitory disequilibrium shocks, the expression in square braces captures the long-run equilibrium relationship between yields and the covariates, and $\varepsilon$ is a random disturbance term. Parameters to be estimated are the disequilibrium (weather) impacts ($\boldsymbol{\beta}^v$), equilibrium (climate) impacts ($\boldsymbol{\eta}^v$), short- and long-run effects of non-climatic variables ($\boldsymbol{\gamma}$ and $\boldsymbol{\lambda}$), and the error-correction parameter ($\theta$), which measuring producers' speed of adjustment to the long-run equilibrium. The parameters $\boldsymbol{\eta}^v$ are vectors of semi-elasticities indicating the percentage by which yields shift relative to their conditional mean levels in response to additional time spent in a given interval. The vectors' elements—the individual coefficient estimates—each capture the distinct marginal effect of exposure within the corresponding interval (e.g., the average impact of an additional hour to 70–80°F versus 80–90°F temperatures). Collectively, the elements of $\boldsymbol{\eta}^v$ flexibly capture $v$'s overall long-run effect as a piecewise linear spline. The shape of the resulting function is identified from

[2] A key example is soil amendments. With agricultural profits, analogous decisions involve inventory adjustments (Deschênes and Greenstone, 2012).

[3] See (Nichell, 1985). To our knowledge, prior climate impacts research employing ECMs (e.g., Blanc, 2012) have not sought to explicitly partition yield variance into the effects of weather versus climate. For a general application of ECMs to agricultural supply response, see Hallam and Zanoli (1993).

the covariation between observed yields and meteorology within each interval, as well as the distribution of observations across intervals over the historical period of the sample. With regard to temperature, the advantage of this approach is that it more precisely resolves the yield impacts of extreme heat relative to the standard degree-day specification (cf. Schlenker and Roberts, 2009). Our dataset is described in the Appendix.

Omitted from Equation 1 is the CFE. Rising $CO_2$ concentrations are a time-varying shock that simultaneously affects yields in all counties. However, there is near-perfect collinearity between the CFE and long-run impacts of other beneficial influences that are strongly trending and spatially homogeneous, such as total factor productivity improvements or technological progress. Data constraints preclude quantification of the latter with accuracy sufficient to construct credible statistical controls.[4] Given the potential for the long-run coefficient on $CO_2$ concentrations to erroneously capture these confounding secular effects, we eschew empirical estimation of the CFE and instead incorporate its effect on our yield projections using relationships based on the literature.

### 2.2 Projecting Yield Impacts of Future Climate Change

Climate change impacts are quantified by combining the fitted values of the equilibrium meteorological parameters ($\hat{\boldsymbol{\eta}}^v$) with meteorological exposures derived from ESM simulations of different warming scenarios. We spatially aggregate simulated 3-hourly fields of temperature, precipitation and soil moisture to the county level ($\tilde{\boldsymbol{T}}_c$, $\tilde{\boldsymbol{P}}_c$ and $\tilde{\boldsymbol{S}}_c$) and bin the results into the $j$, $k$ and $l$ intervals (respectively) over crop growth stages in current and future growing seasons to generate exact analogues of the regression covariates, $\tilde{\xi}^v$.[5] Yields under irrigated and rainfed management regimes (indexed by $v = \{I, R\}$) exhibit different responses to precipitation and moisture as well as elevated $CO_2$. Accordingly, we model them separately (see Appendix D), specifying rainfed impacts as a function of temperature, precipitation, soil moisture and ambient $CO_2$ concentrations ($\tilde{C}$), and irrigated impacts as a functions of temperature and $CO_2$:

$$\psi_i^R\left(\tilde{\boldsymbol{T}}_c, \tilde{\boldsymbol{P}}_c, \tilde{\boldsymbol{S}}_c, \tilde{C}\right) = \sum_g \left\{ \sum_j \hat{\eta}_{i,j,g}^T \tilde{\xi}_{j,g,c}^T + \sum_k \hat{\eta}_{i,k,g}^P \tilde{\xi}_{k,g,c}^P + \sum_l \hat{\eta}_{i,l,g}^S \tilde{\xi}_{l,g,c}^S \right\} + \log F_i^R\left(\tilde{C}\right) \tag{2a}$$

$$\psi_i^I\left(\tilde{\boldsymbol{T}}_c, \tilde{C}\right) = \sum_g \left\{ \sum_j \hat{\eta}_{i,j,g}^T \tilde{\xi}_{j,g,c}^T \right\} + \log F_i^I\left(\tilde{C}\right) \tag{2b}$$

Here, $F_i^m$ is a concave function that captures the differential benefits of $CO_2$ fertilization un-

[4] Absent specific indicators of technological advance (e.g. patent stocks), productivity improvements are customarily modeled using a time trend.

[5] Comparing current and future climates that are both simulated (as opposed to comparing simulated future climate against observed current climate) is a way of minimizing the impact of potential bias in ESM projections.

der different moisture stress conditions, based on Hatfield *et al.* (2011) and McGrath and Lobell (2013). Our calibration of the CFE index is documented in the Appendix D.

The terms $\psi^m_{i,c}$ indicate the partial effects of climate on the logarithm of irrigated and rainfed yields. Our normalized decadal index of climate impact is the yield ratio:

$$\psi_{i,c} = \mathbb{E}\left[\begin{array}{l} \bar{\phi}^R_c \exp\left\{\begin{array}{l} \psi^R_i\left(\tilde{\boldsymbol{T}}^{Future}_c, \tilde{\boldsymbol{P}}^{Future}_c, \tilde{\boldsymbol{S}}^{Future}_c, \tilde{C}^{Future}\right) \\ \\ -\psi^R_i\left(\tilde{\boldsymbol{T}}^{Current}_c, \tilde{\boldsymbol{P}}^{Current}_c, \tilde{\boldsymbol{S}}^{Current}_c, \tilde{C}^{Current}\right) \end{array}\right\} \\ \\ +\bar{\phi}^I_c \exp\left\{\psi^R_i\left(\tilde{\boldsymbol{T}}^{Future}_c, \tilde{C}^{Future}\right) - \psi^R_i\left(\tilde{\boldsymbol{T}}^{Current}_c, \tilde{C}^{Current}\right)\right\} \end{array}\right] \tag{3}$$

in which $\mathbb{E}$ is the expectation operator and $\bar{\phi}^v_c$ denotes the average shares of irrigated and rainfed cultivation from the MIRCA dataset (Portmann *et al.*, 2010), which we treat as remaining fixed into the future (this assumption is discussed in the Appendix). $\Psi_{i,c}$ is interpretable as the climatically-attributable fractional change in a county's average yield relative to its own conditional mean.[6] Accordingly, holding the current geographic distribution of harvested area constant as well, the change in production of each crop is simply the quantity $\Psi_{i,c} \times Y^{Current}_{i,c}$.

Our simulated meteorological fields and ambient $CO_2$ concentrations are taken from the CIRA project (Waldhoff *et al.*, 2015), a 15-member ensemble of simulations using the MIT Integrated Global System Model-Community Atmosphere Model (IGSM-CAM) modeling framework (Monier *et al.*, 2013).[7] CIRA is underlain by three consistent socioeconomic and emissions scenarios: a reference scenario with unconstrained emissions and two climate stabilization scenarios that impose uniform global taxes on greenhouse gases to limit total radiative forcing to 4.5 W m$^{-2}$ and 3.7 W m$^{-2}$ by century's end. Reductions in climate damages to agriculture in moving from the reference to the policy scenarios are interpretable as the benefits of GHG mitigation, and the associated differences in US agriculture sector output and relative prices are crucial to our cost estimates (Paltsev *et al.*, 2015). For each emission scenario, IGSM-CAM was run with different values of climate sensitivity and aerosol forcing, and different representations of natural variability, resulting in a 60-member ensemble (Monier *et al.*, 2015). We focus on simulations with a climate sensitivity of 3°C, with each scenario run as a 5-member ensemble with different representations of natural variability in an attempt to span the potential range of natural variability. Spatially disaggregating these projections to the county scale and using Equations 2 and 3 enables us to calculate yield impacts at the middle and the end of the century (2036–2065 and 2086–2115) for each combination of scenario and ensemble member. We analyze 30-year time periods over 5 ensemble members with different representations of natural variability, resulting in a total of 150 years defining changes from the present day to the middle and end of the century, in order to obtain ro-

[6] If $\Psi_i \in (0, 1)$ the shift in the mean climatic exposure reduces crop productivity, and increases it otherwise.

[7] IGSM-CAM links the IGSM, an integrated assessment model coupling an earth system model of intermediate complexity (EMIC) to a global economic model (MIT-EPPA, Paltsev *et al.*, 2005), with the National Center for Atmospheric Research (NCAR) Community Atmosphere Model (CAM, Collins *et al.*, 2006).

bust estimates of climate impacts on yield where the anthropogenic signal is extracted from the noise associated with natural variability.

## 3. RESULTS

### 3.1 Yield Responses to Climate Change

Our long-run estimates are, for the most part, broadly consistent with current agronomic understanding of weather effects on field crop yields. Space constraints preclude detailed description of these results for all five crops. We highlight our findings for corn and consign the remaining results in the Appendix E. Figure 1 shows corn's meteorological yield response functions (panel A) and the changes in exposure to weather conditions experienced by an average county in our three scenarios circa 2050 and 2100 (panels B and C). Yields decline precipitously with extreme temperature (Schlenker and Roberts, 2009; Burke and Emerick, 2015), but stratification of our responses by growth phase highlights the large impact in the first half of the growing season (Ortiz-Bobea *et al.*, 2013)—each additional 3-hour period below 15°C increases yields by as much as 0.005% relative to their conditional mean, but similar exposure above 40°C triggers a reduction of more than 0.01%. Over the second half of the growing season, temperatures cause slight yield declines below the latter threshold but a marked increase above (as much as 0.01% per 3 hours).[8] A key point of divergence with prior results is our finding that yields increase strongly and approximately linearly with precipitation, with trace amounts associated with slight declines but 3-hour extreme exposures ($>$15 mm) increasing yields by up to 0.01% (0.015%) in the early (late) sub-periods. The instantaneous soil moisture response exhibits a generalized inverse U shape with an apex at the conditional mean exposure, a very slight negative influence over most of its range and sharply negative impact at the upper extreme ($> 35\,\mathrm{kg\,m^{-2}}$), with reduction of up to 0.004% (0.008%) in the early (late) sub-periods. Other crops' responses share many of these characteristics (Figs. A2–A5).[9]

GHG mitigation's broad influence is to partially reverse these shifts in probability mass (the green and blue bars). Across meteorological variables, the most common pattern is for the bars indicating the policy scenarios to be of smaller magnitude but mostly opposite sign to those cor-

[8] The positive late response to high temperature is not the result of outlying observations. Historically, corn has regularly been exposed to this kind of heat, albeit in tiny amounts. In 23% of our 136,000 county x year observations, corn was exposure to one or more 3-hour periods with $T > 43°C$ in the second half of the growing season, covering 2307 out of 2842 counties and all the years of our sample. Using simpler empirical models, (Blanc and Sultan, 2015, Figs. C1–C4) uncover similar beneficial yield responses to late extreme heat in the results of ISI-MIP GGCMs. Work remains to be done to understand the mechanisms responsible for this phenomenon, both in GGCMs and the field.

[9] We find negative and strongly nonlinear temperature sensitivity of sorghum, soybeans, and, to a lesser extent, wheat—especially in the first half of the growing season (cf. Tack *et al.*, 2015). For the most part, the long-run effect of precipitation is positive or statistically insignificant over most of its range (especially in the second half of the growing period). Exceptions are the significant negative impacts of early extreme precipitation on soybeans and wheat. Long-run soil moisture responses peak apex at the modal exposure, suggesting detrimental yield impacts of soil waterlogging as well as drying, with the exception of cotton early in the growing season. These results are generally in line with recent empirical findings. A shortcoming of our model is its omission of freezing temperatures and the associated negative response of wheat yields, whose amelioration in a warming climate provides an offsetting beneficial effect (Tack *et al.*, 2015).

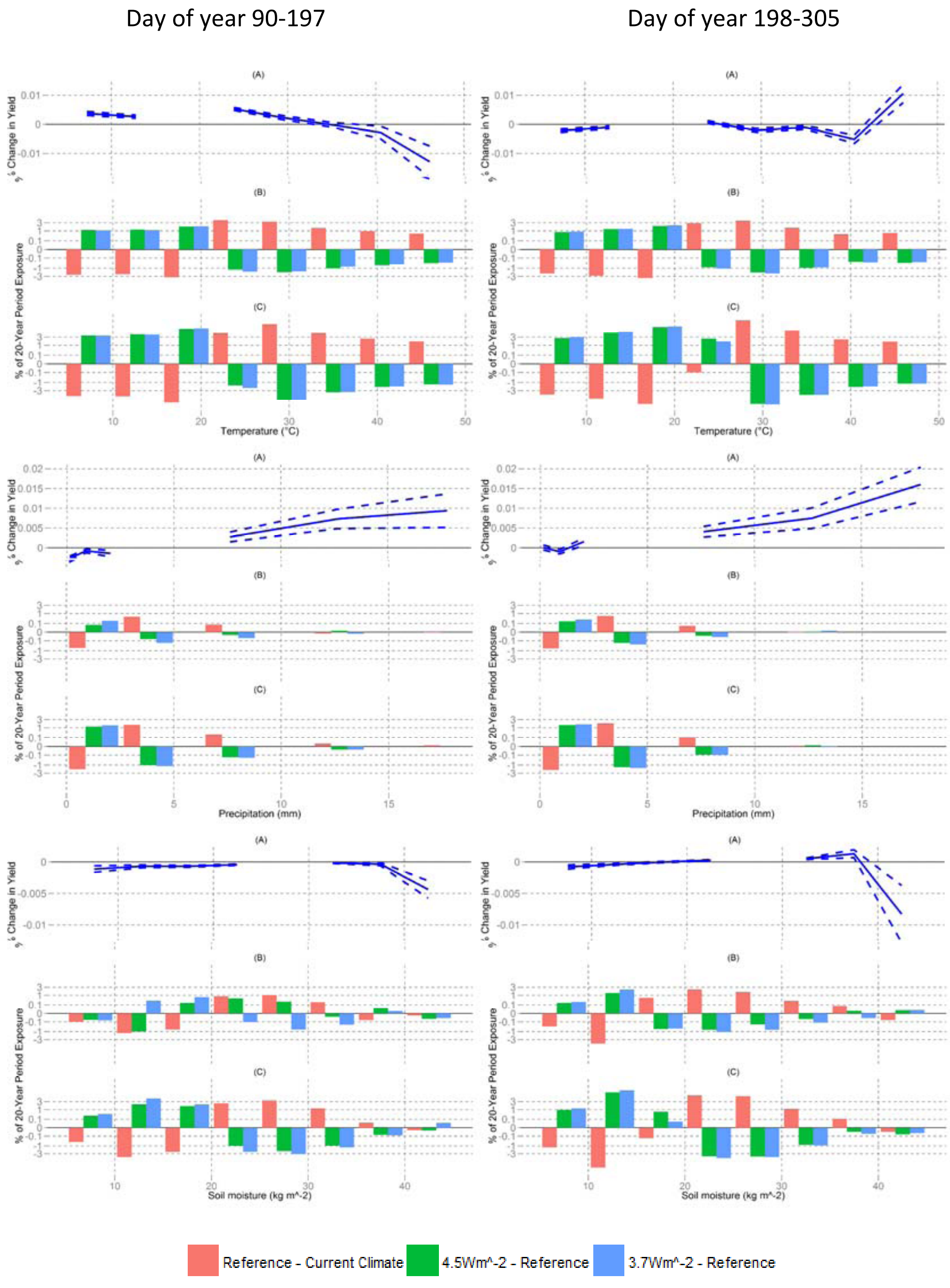


**Figure 1.** Corn empirical yield response functions (A) and the change in the distributions of average county temperature, precipitation and soil moisture exposure circa year 2050 (B) and 2100 (C), over growing season sub-periods. Gaps in splines correspond to omitted modal intervals. Histograms show the differences in the distributions of exposure between the no-policy reference scenario and the current climate, and between the 4.5 W m$^{-2}$ and 3.7 W m$^{-2}$ GHG mitigation scenarios and the reference case. The vertical axes of the differenced exposure distributions have non-linear scales to better illustrate the shifts in meteorology due to climate change.

responding to the reference case. Crucially, such reversals are not always beneficial. In the reference scenario, exposure to low precipitation declines in both halves of the growing season circa 2100, and, relative to this outcome, GHG emission mitigation increases the average frequency of such dry episodes, with adverse late season yield impacts. Similarly, increases in large precipitation events under the reference scenario improve yields, but mitigation reduces these increases, curtailing this particular benefit from unmitigated climate change. Finally, as indicated in the Appendix (Figure D1), a pervasive consequence of mitigation is the reduction in the CFE and its attendant yield benefits.

### 3.2 Projected Changes in Crop Yields and Production

Conditions within individual counties can diverge markedly from the aforementioned average changes in exposure. Maps of projected yield changes in Figure 2 indicate the spatial patterns of the threat to the five major crops posed by unmitigated climate change, as well as the substantial threat reduction due to moderate mitigation. Panel A shows the counties where crop production is concentrated, while panels B and C illustrate the percentage changes in yields calculated using Equation 3. All crops experience both beneficial and adverse effects, depending on the region. In the reference scenario, wheat yields increase in the northwest and decline in the south central and southwest regions circa 2050, a pattern that intensifies markedly toward century's end. For the remaining crops, the patterns of impact tend to follow the north-south temperature gradient. Soybean and corn yields suffer pronounced negative impacts in the South and the Mississippi River Valley that first lessen before turning positive with proximity to Canada. For cotton, the largest adverse effects are dispersed across the crescent of southernmost counties, while for sorghum negative impacts are concentrated in the southwest. The reductions in changes in climatic variables as a consequence of mitigation policies attenuate the amplitude of beneficial as well as adverse yield shocks. Even a $4.5\,\mathrm{W\,m^{-2}}$ GHG stabilization policy limits impacts to $\pm 10\%$ from baseline levels in the majority of cultivated counties. Results for the stringent $3.7\,\mathrm{W\,m^{-2}}$ scenario (not shown) are similar but further accentuated.

However, the risk to agricultural supply arises out of the spatial intersection of yield shocks and patterns of crop production in future decades when climatic changes occur. Although the latter will likely differ from today, given the challenges that attend prediction of agriculture's future geographic distribution (see, e.g., Ortiz-Bobea and Just, 2012; Iizumi and Ramankutty, 2015), we follow the empirical literature in assuming that irrigated and rainfed crop cultivation will continue to follow the current geographic pattern in panel A. We summarize the impacts at the scale of US climate regions in Table 1.

Under reference warming, circa 2050, there are increases in yields of corn and sorghum, declines in wheat and soybeans, and mixed impacts on cotton in the regions where production of these crops is concentrated. Climate impacts that manifest in one or two regions at mid-century often spread geographically by 2100, with production in regions that suffer early adverse impacts (e.g., the southeast, and, to a lesser extent, south central regions) often experiencing further declines. Mitigation often only softens the blow in regions with the largest percentage losses, and, paradoxically, changes in weather patterns associated with stringent emission reductions may

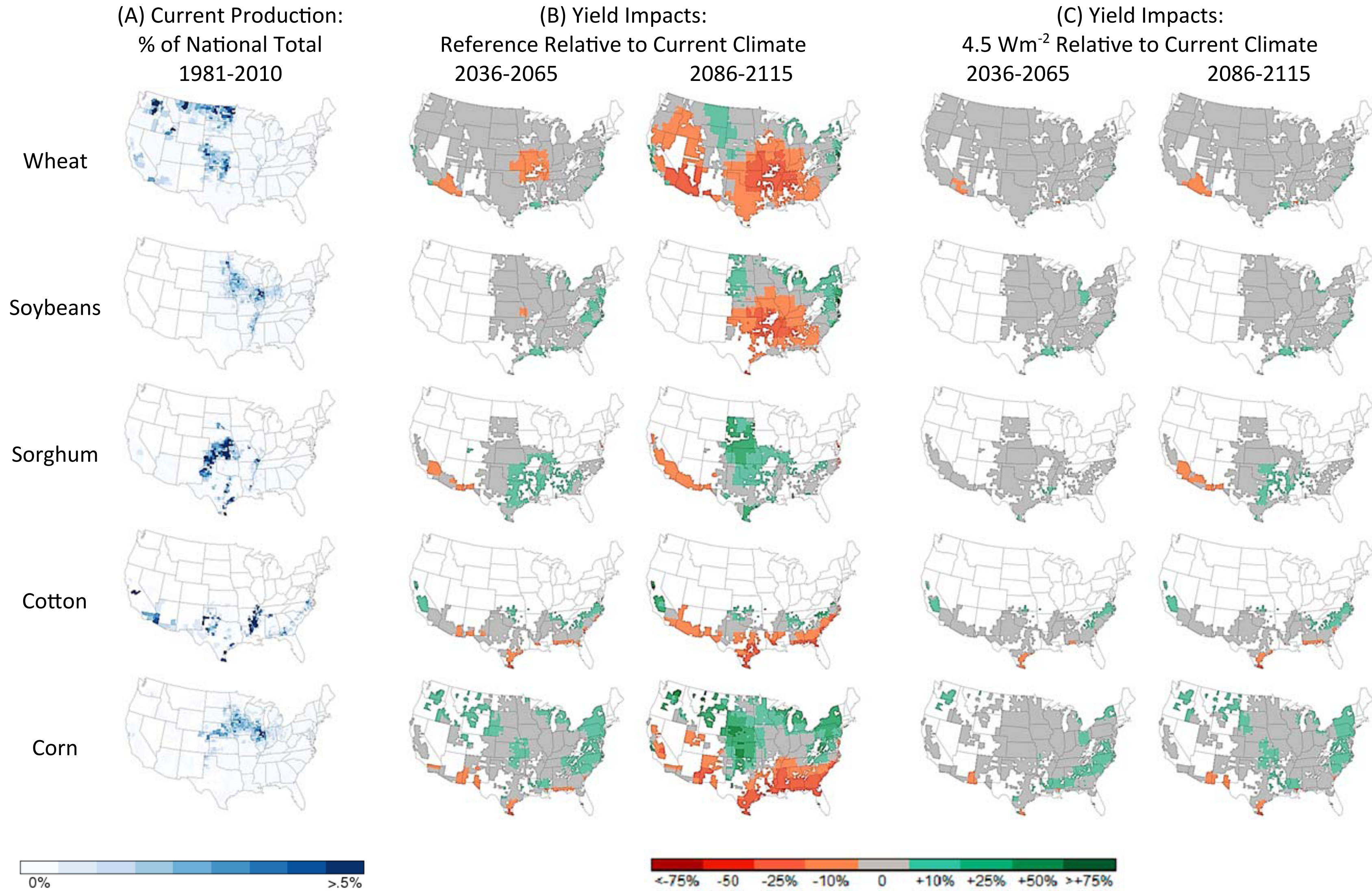


**Figure 2.** Geographic distributions of 1980–2010 crop production (A), and % change in yields of five major US crops relative to current climate circa years 2050 and 2100, under a no-policy reference scenario (B) and a moderate GHG mitigation scenario (C).

**Table 1.** Changes in crop production (%) relative to current climate in the no-policy reference and GHG mitigation scenarios, circa years 2050 and 2100: by US climate regions. Square braces: changes in output from the reference scenario; shaded cells: losses relative to the current period (in cells with square braces, relative to reference scenario); bold: major producing regions.

| | Output Share (%) | 2036-2065 | | | | | 2086-2115 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Ref | 4.5 $Wm^{-2}$ | | 3.7 $Wm^{-2}$ | | Ref | 4.5 $Wm^{-2}$ | | 3.7 $Wm^{-2}$ | |
| | | Wheat | | | | | | | | | |
| Southeast | 3.2 | 3.7 | 4.7 | [1.0] | 3.6 | [-0.1] | -4.8 | 4.0 | [8.7] | 2.0 | [6.8] |
| Southwest | 4.9 | -2.9 | -0.9 | [2.0] | -0.8 | [2.1] | -3.2 | -0.8 | [2.3] | -1.1 | [2.1] |
| **South** | **30.8** | **-6.8** | **-1.4** | **[5.4]** | **-2.3** | **[4.5]** | **-18.3** | **-2.9** | **[15.4]** | **-4.5** | **[13.8]** |
| West | 2.1 | -1.1 | -0.7 | [0.4] | -0.6 | [0.5] | -8.1 | -1.7 | [6.4] | -0.7 | [7.4] |
| Northeast | 1.2 | 6.7 | 5.1 | [-1.7] | 4.0 | [-2.7] | 21.3 | 5.7 | [-15.6] | 5.1 | [-16.2] |
| Northwest | 12.7 | -5.1 | -3.0 | [2.1] | -2.7 | [2.4] | -9.7 | -3.9 | [5.8] | -3.7 | [6.0] |
| Central | 11.0 | -6.3 | 0.6 | [6.9] | -1.0 | [5.3] | -18.8 | -3.0 | [15.7] | -2.7 | [16.0] |
| E.N. Central | 6.2 | 0.5 | 2.1 | [1.7] | 1.6 | [1.2] | 0.7 | 1.4 | [0.8] | 1.9 | [1.2] |
| **W.N. Central** | **27.9** | **-0.3** | **0.7** | **[1.1]** | **0.5** | **[0.8]** | **4.2** | **0.7** | **[-3.5]** | **0.3** | **[-4.0]** |
| | | Soybeans | | | | | | | | | |
| Southeast | 4.4 | 8.9 | 7.9 | [-1.0] | 6.5 | [-2.4] | 4.2 | 8.2 | [4.0] | 5.2 | [1.0] |
| Southwest | | | | | | | | | | | |
| South | 11.6 | -3.9 | 0.8 | [4.7] | -0.7 | [3.2] | -23.0 | -1.2 | [21.9] | -3.5 | [19.5] |
| West | | | | | | | | | | | |
| Northeast | 1.8 | 12.1 | 8.1 | [-4.0] | 6.7 | [-5.4] | 38.1 | 9.8 | [-28.4] | 8.1 | [-30.0] |
| Northwest | | | | | | | | | | | |
| **Central** | **41.1** | **-2.7** | **3.3** | **[6.0]** | **1.3** | **[4.0]** | **-13.0** | **0.2** | **[13.2]** | **-0.1** | **[12.9]** |
| **E.N. Central** | **29.4** | **-1.7** | **3.9** | **[5.6]** | **2.3** | **[4.0]** | **-4.1** | **2.3** | **[6.3]** | **1.1** | **[5.1]** |
| W.N. Central | 11.8 | -1.5 | 3.2 | [4.6] | 1.9 | [3.4] | 4.4 | 2.5 | [-1.9] | 0.3 | [-4.1] |
| | | Sorghum | | | | | | | | | |
| Southeast | 1.7 | 9.4 | 6.6 | [-2.9] | 6.4 | [-3.1] | 4.9 | 7.1 | [2.2] | 4.5 | [-0.4] |
| Southwest | 2.6 | -1.2 | -2.3 | [-1.0] | -2.9 | [-1.6] | 6.9 | -1.4 | [-8.3] | -2.9 | [-9.7] |
| **South** | **70.7** | **6.5** | **2.7** | **[-3.9]** | **2.1** | **[-4.4]** | **18.1** | **4.9** | **[-13.2]** | **1.2** | **[-16.9]** |
| West | 0.4 | -3.8 | -0.9 | [2.8] | -0.6 | [3.2] | -16.0 | -3.0 | [13.1] | -1.1 | [14.9] |
| Northeast | 0.0 | -9.8 | -5.8 | [4.1] | -6.3 | [3.5] | -25.7 | -8.2 | [17.5] | -7.3 | [18.4] |
| Northwest | | | | | | | | | | | |
| Central | 10.7 | 9.5 | 4.7 | [-4.8] | 5.4 | [-4.1] | 10.9 | 7.4 | [-3.5] | 4.3 | [-6.6] |
| E.N. Central | 0.2 | 3.6 | 3.7 | [0.1] | 3.6 | [0.0] | 11.1 | 5.0 | [-6.1] | 3.2 | [-7.9] |
| **W.N. Central** | **13.6** | **6.7** | **4.0** | **[-2.7]** | **3.4** | **[-3.3]** | **29.1** | **7.0** | **[-22.1]** | **3.0** | **[-26.1]** |
| | | Cotton | | | | | | | | | |
| **Southeast** | **18.2** | **4.8** | **6.5** | **[1.7]** | **4.7** | **[-0.2]** | **-10.6** | **7.2** | **[17.8]** | **3.9** | **[14.6]** |
| Southwest | 5.2 | -6.7 | -3.0 | [3.8] | -2.6 | [4.1] | -15.5 | -5.3 | [10.3] | -5.0 | [10.5] |
| **South** | **56.9** | **-2.8** | **0.7** | **[3.6]** | **0.2** | **[3.0]** | **-8.4** | **-1.1** | **[7.2]** | **-1.4** | **[7.0]** |
| West | 12.7 | 21.1 | 11.9 | [-9.2] | 11.2 | [-9.9] | 27.8 | 18.0 | [-9.8] | 12.3 | [-15.5] |
| Northeast | | | | | | | | | | | |
| Northwest | | | | | | | | | | | |
| Central | 7.0 | 8.7 | 8.6 | [-0.1] | 4.9 | [-3.8] | 6.0 | 8.1 | [2.0] | 2.9 | [-3.1] |
| E.N. Central | | | | | | | | | | | |
| W.N. Central | | | | | | | | | | | |
| | | Corn | | | | | | | | | |
| Southeast | 2.4 | 10.2 | 10.8 | [0.6] | 8.8 | [-1.4] | -15.8 | 10.5 | [26.2] | 6.4 | [22.1] |
| Southwest | 1.5 | 2.1 | 1.6 | [-0.5] | 1.9 | [-0.2] | 22.0 | 3.1 | [-19.0] | 1.9 | [-20.1] |
| South | 6.9 | 1.9 | 2.9 | [1.0] | 2.2 | [0.3] | 10.4 | 3.7 | [-6.7] | -0.9 | [-11.3] |
| West | 0.3 | -2.2 | -0.4 | [1.7] | -0.6 | [1.6] | -8.9 | -2.1 | [6.8] | -1.2 | [7.6] |
| Northeast | 2.6 | 11.7 | 8.2 | [-3.5] | 5.6 | [-6.1] | 21.4 | 10.5 | [-10.9] | 8.0 | [-13.4] |
| Northwest | 0.3 | 20.2 | 13.3 | [-6.9] | 12.8 | [-7.4] | 28.6 | 17.6 | [-11.0] | 14.1 | [-14.5] |
| **Central** | **34.9** | **6.6** | **6.1** | **[-0.6]** | **4.3** | **[-2.4]** | **0.0** | **5.6** | **[5.6]** | **3.9** | **[3.8]** |
| **E.N. Central** | **34.7** | **6.3** | **4.9** | **[-1.4]** | **5.3** | **[-1.0]** | **12.5** | **7.2** | **[-5.3]** | **4.3** | **[-8.3]** |
| W.N. Central | 16.2 | 7.2 | 4.8 | [-2.4] | 5.3 | [-1.9] | 29.3 | 7.6 | [-21.7] | 3.5 | [-25.8] |

have smaller ameliorative impacts (cf. south, southeast and central sorghum and corn), likely due to the interplay between the impact of changes in meteorological variables and the CFE. Conversely, climate change improves yields in the cooler northeast, northwest, and, less reliably, north central areas around mid-century, with declines in the pool of regions experiencing beneficial weather as warming proceeds. Mitigation offsets output declines from regions experiencing losses at the cost of curtailing gains to those benefiting from climate change. However, rarely does mitigation transform gains under the reference into outright losses: more commonly regions that gain experience smaller benefits.

Our projected percentage changes in aggregate yield understate those of prior studies, although a clean comparison is elusive because of differences in the scenarios of future warming and their meteorological consequences as elaborated by ESMs (cf. Table A3). Our inclusion of the CFE accounts for some of this divergence. Re-running our projections without the CFE[10] results in yield losses that are 20% larger for wheat and 300% larger for cotton, and gains that are 100% larger for soybean and 10-15% smaller for corn and sorghum (Table A2). More consequential are our findings of countervailing effects of extreme heat on corn yields (adverse early, beneficial late), and the general importance of precipitation. The latter is particularly important given that our estimates assume no water stress, and therefore no impact of projected changes in precipitation or soil moisture, on the irrigated fraction of the crop in each county. Relative to the customary method of applying a single fitted yield response function everywhere, our approach reduces yield losses (gains) in regions experiencing precipitation and soil moisture declines (increases).

### 3.3 Economic Costs of Agricultural Impacts and Benefits of GHG Mitigation

The implications for aggregate climate damage costs and GHG mitigation benefits are summarized in Table E2. Costs (negative entries) and benefits (positive entries) are assessed by establishing two baselines from which to compute the absolute changes in output that correspond to US-wide percentage changes. Panel A (which collapses Table 1) demonstrates that, under reference warming, adverse national average yield impacts are dominated by wheat, soybeans and, toward century's end, cotton. Conversely, corn and sorghum experience large increases in national average yield. Panel B shows the result of a comparative static calculation of the associated costs and benefits of climate change if crop production and prices remain at today's levels. Output losses (i) follow the reference pattern in Panel A, but negative impacts impacts are lessened for wheat and reversed for soybeans by mitigation, which reduces warming to beneficial levels. The corresponding economic impacts (ii) are expressed as changes in revenue, calculated by multiplying the quantity shocks by each crop's 1981–2010 average real farmgate price. Broadly echoing findings in Deschênes and Greenstone (2007), climate change has a net beneficial impact which is modest at mid-century ($1B) but becomes negligibly small by 2100. Relative to the reference, moderate mitigation generates additional annual benefits of $1B in 2050 and $2B in 2100, while the annual benefits of stringent migration are smaller: $0.6B by 2050 and $0.8B by 2100. Panel B's estimates incorporate future increases in production, and associated price changes, as simulated by MIT-EPPA's CIRA runs. Impacts are identical in sign, but expansions in crop output

[10] This is achieved simply by setting $\kappa_i^m = 0$ in Equation A9.

and revenue increase the magnitude of costs and benefits.[11] Net annual benefits under reference warming are still small: $3B circa 2050 and $1B circa 2100. Mitigation gives rise to modest annual benefits of $3B (2050) and $17B (2100) for moderate mitigation, or $1B (2050) and $7B (2100) for stringent mitigation.

**Table 2.** Aggregate annual changes in crop yields, production and associated gross costs and benefits relative to current climate in the no-policy reference scenario, and aggregate avoided changes in crop yields and associated costs and benefits under GHG mitigation scenarios, circa years 2050 and 2100. (A) aggregate yield changes; (B) prices and quantities in current agricultural system; (C) prices and quantities scaled according to future growth simulated by the MIT-EPPA model's CIRA simulations.

| | 2036-2055 | | | 2086-2115 | | |
|---|---|---|---|---|---|---|
| | Ref | 4.5 $Wm^{-2}$ | 3.7 $Wm^{-2}$ | Ref | 4.5 $Wm^{-2}$ | 3.7 $Wm^{-2}$ |
| | A. Average Change in Yield Relative to Current Climate (%) | | | | | |
| Wheat | -3.5 | -0.3 | -0.8 | -7.9 | -1.3 | -1.9 |
| Soybeans | -1.6 | 3.5 | 1.8 | -7.8 | 1.4 | 0.3 |
| Sorghum | 6.7 | 3.0 | 2.6 | 18.1 | 5.3 | 1.7 |
| Cotton | 2.2 | 3.6 | 2.6 | -3.5 | 3.2 | 1.5 |
| Corn | 6.4 | 5.3 | 4.8 | 10.4 | 6.6 | 3.8 |
| | B. Current Agricultural System | | | | | |
| | (i) Average Change in Production Relative to Current Climate ($10^6$ tons) | | | | | |
| Wheat | -2.1 | -0.2 | -0.5 | -4.9 | -0.8 | -1.2 |
| Soybeans | -1.1 | 2.3 | 1.2 | -5.2 | 1.0 | 0.2 |
| Sorghum | 1.1 | 0.5 | 0.4 | 2.9 | 0.9 | 0.3 |
| Cotton | 0.1 | 0.1 | 0.1 | -0.1 | 0.1 | 0.1 |
| Corn | 14.9 | 12.3 | 11.0 | 24.1 | 15.2 | 8.7 |
| | (ii) Impact Gross Cost (negative) or Benefit (positive) in Reference Scenario; Mitigation Net Benefit (positive) or Cost (negative) in Policy Scenarios (2010 $ M) | | | | | |
| Wheat | -388 | 360 | 297 | -887 | 741 | 673 |
| Soybeans | -336 | 1050 | 698 | -1608 | 1904 | 1664 |
| Sorghum | 106 | -58 | -65 | 288 | -204 | -261 |
| Cotton | 138 | 85 | 24 | -222 | 424 | 313 |
| Corn | 1502 | -258 | -390 | 2431 | -892 | -1550 |
| **Total** | **1022** | **1180** | **563** | **2** | **1973** | **838** |
| | C. Projected Future Agricultural System | | | | | |
| | (i) Average Change in Production ($10^6$ tons) | | | | | |
| Wheat | -5.5 | -0.4 | -1.1 | -32.4 | -4.6 | -5.8 |
| Soybeans | -2.8 | 5.5 | 2.6 | -34.3 | 6.3 | 1.2 |
| Sorghum | 2.8 | 1.2 | 0.9 | 19.5 | 5.7 | 1.8 |
| Cotton | 0.2 | 0.3 | 0.2 | -0.3 | 0.3 | 0.1 |
| Corn | 37.9 | 29.4 | 24.6 | 158.9 | 100.6 | 57.5 |
| | (ii) Impact Gross Cost (negative) or Benefit (positive) in Reference Scenario; Mitigation Net Benefit (positive) or Cost (negative) in Policy Scenarios (2010 $ M) | | | | | |
| Wheat | -1232 | 1170 | 1011 | -8395 | 7368 | 7475 |
| Soybeans | -1065 | 3251 | 2143 | -15230 | 18442 | 17125 |
| Sorghum | 336 | -199 | -231 | 2726 | -1973 | -2682 |
| Cotton | 439 | 229 | 12 | -811 | 1539 | 1199 |
| Corn | 4765 | -1092 | -1728 | 23016 | -8642 | -15957 |
| **Total** | **3243** | **3360** | **1207** | **1305** | **16733** | **7160** |

[11] Relative to today, composite agricultural output is projected to increase by a factor of 2.5 by 2050 and 6.5 by 2100, with real composite agricultural prices increasing by 25% and 44%, respectively.

## 4. DISCUSSION AND CONCLUSIONS

By combining empirical analysis with integrated economic and climate projections, we demonstrate that climate change effects on US crop yields are likely to be slight around mid-century but substantially costly near century's end. Regions where climates are already warm suffer losses, but cooler regions enjoy gains. Declines in production are concentrated in soybeans, cotton, and wheat, but these are partially offset by increased output of corn and sorghum. Reductions in radiative forcing from GHG mitigation generally offset output declines from regions and crops that experience losses, but at the cost of curtailing gains to those that benefit from climate change.

As summarized in Figure 3, our results suggest that the overall effect of mitigation policies on agricultural revenues will be positive, but the magnitude is sensitive to the beneficial impacts of $CO_2$ fertilization. Without CFE, the impact of unmitigated climate change flips sign, incurring annual net costs of \$3B circa 2050 and \$18B circa 2100.. This amplifies the positive effect of emission reductions, increasing the benefits by \$1.4B (2050) and \$10B (2100) for moderate mitigation, and by \$1.1B (2050) and \$13B (2100) for stringent mitigation. These estimates, which should be considered upper bounds on the costs of climate change impact and corresponding emissions reduction benefits, highlight the critical importance of assumptions regarding the CFE. They are also somewhat larger than, but in the same general range as, climate change damages generated by prior studies (see Table A2), though simple comparisons of total dollar values are not appropriate given the use of different impact endpoints (land values, agricultural profits, non-monetized yields, or affected crops) and climate change projections, as well as the lack of accounting for the CFE. As a case in point, the study most closely related to ours—Beach *et al.* (2015)—employs a crop model forced by the CIRA IGSM-CAM simulations to construct gross-of-CFE changes in corn, soybean and wheat yields and which are then applied as exogenous shocks in a partial equilibrium simulation of the US agriculture and forestry sector. Yield impacts are mostly positive in the reference scenario and become more beneficial with stringent mitigation, over 2015–2100 increasing cumulative agricultural surplus by (2005) \$45B—or an average annual mitigation benefit of \$0.5B.

Our analysis represents an advance over current approaches to quantifying the costs and benefits of climate change. We use projections of the future state of the agricultural economy using CGE model output whose simulated growth rates of agricultural output and prices are consistent with the economic expansion, general equilibrium price and quantity effects of mitigation policies, and concomitant GHG emissions, radiative forcing and meteorological changes that determine the shocks to crop yields in the decades in which these impacts occur. By contrast, empirical studies' comparative statics valuation of impacts as changes in agricultural revenues or profits under current production and prices can dramatically understate costs (see Table E2). Modeling studies that simply impose GGCM-simulated yield changes onto economic models risk being inconsistent with future economic conditions, GHG emissions, and the climatic forcing of yield shocks that we argue is essential to consistent estimation of costs and benefits. However, the critical feature of such model-based economic consequence analyses is the additional uncertainty they introduce by simulating the moderating effects of adaptation via market mediated price and quantity adjustments (cf. Beach *et al.*, 2015). Although adaptation will almost surely occur, its

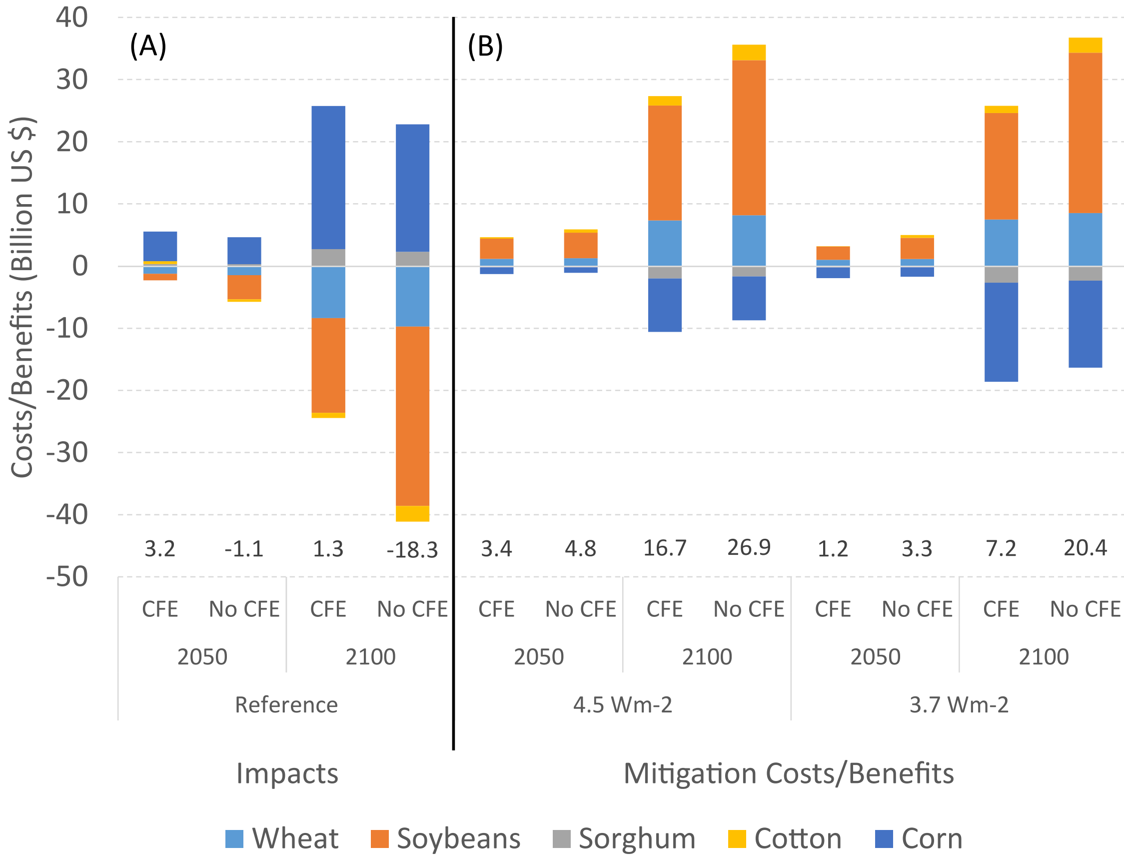


**Figure 3.** Annual costs (negative entries) and benefits (positive entries) of climate change impacts and mitigation on US agriculture with and without $CO_2$ fertilization, circa 2050 and 2100. (A) Impacts by crop (total shown at bottom). (B) Costs and benefits of 4.5 W m$^{-2}$ and 3.7 W m$^{-2}$ stabilization policies by crop (total shown at bottom).

associated indirect economic costs and benefits are poorly characterized and difficult to estimate, yet require accurate quantification to avoid potential double-counting when estimating the net benefit of mitigation. Our deliberately conservative approach is therefore to exclude the effects of future adaptation from our cost-benefit calculations. Instead, we value the impact of climate change under the economic conditions likely to prevail at the instant such a shock occurs, before producers and consumers have an opportunity to react (Fisher-Vanden *et al.*, 2013).

Nevertheless, several caveats to our analysis remain. Our narrow focus on well-documented impact pathways omits myriad indirect climate-related changes in crops' growing environment (e.g., ozone concentrations, diseases, pathogens and weeds) on which the literature provides less guidance regarding yield responses. Space constraints preclude a full uncertainty analysis of the underlying economic assumptions in the MIT EPPA model and the climate system response, and particularly the CFEs yield benefits, which were difficult to bound (see Appendix D). The dependence of yield changes on the assumption of perfect water application in currently irrigated areas highlights the sensitivity of our cost benefit projections to the availability of water resources sufficient for irrigation as crop production expands out to century's end. The latter, while driven by shifting precipitation patterns, requires hydrological analysis (e.g., future water infrastructure and efficiency assumptions, changes in runoff and discharge, competition with growing municipal and industrial demands, groundwater resource development and depletion) to determine how, and where, it might influence our results. Finally, the CGE model that we use resolves future changes in aggregate agricultural activity, not individual crops. Research is ongoing to address these issues.

More broadly, our results illustrate the potential of reduced-form empirical analysis as an alternative to GGCMs in evaluating climate change impacts on agriculture (Rosenzweig *et al.*, 2014; Nelson *et al.*, 2014). Although crop models incorporate both detailed process-based understanding of crop physiology and the ameliorating effects of a plethora of management options, concerns regarding their accuracy in capturing crop yields' responses to meteorological change (Hertel and Lobell, 2014) have been slow to prompt extensive testing, especially at the geographic scales examined here.[12] Our methodology can usefully be applied to model the relationships between GGCM simulated yields and their climatic drivers, and thereby facilitate head-to-head comparisons that can lead to more robust estimates of impact response, future yield shocks, and associated economic costs and benefits.

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[12] Fortunately, this situation is beginning to change—see, e.g., Lobell and Burke (2010), Estes *et al.* (2013a,b), Blanc and Sultan (2015) and Montesino-San Martín *et al.* (2015).

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## APPENDIX A: Theoretical Foundation

Hallam and Zanoli (1993) apply Nichell (1985)'s theoretical dynamic model to agricultural supply response. Following their exposition, consider a farmer who pursues a long-run equilibrium level of yield, $y^*$. She chooses the actual level of yield, $y$, over an infinite horizon [$t$,$t$+1,..., $t$+$\tau$,...,$\infty$] so as to jointly minimize the divergence from the optimum, and the interannual variability due to random weather shocks. In period $t$, these twin objectives are captured by the following forward-looking quadratic loss function:

$$L = \sum_{\tau=0}^{\infty} \rho^{\tau} \left[\varphi_1 \left(y_{t+\tau} - y^*_{t+\tau}\right)^2 + \left(y_{t+\tau} - y_{t+\tau-1}\right)^2 - 2\varphi_2 \left(y_{t+\tau} - y_{t+\tau-1}\right)\left(y^*_{t+\tau} - y^*_{t+\tau-1}\right)\right] \tag{A1}$$

where $\varphi_1$,$\varphi_2$>0 are loss coefficients and $\rho \in (0, 1)$ is the discount factor. The terms in square braces are: first, losses that increase quadratically as yields diverge from the optimal level; second, quadratic interannual adjustment costs (on which losses are normalized); and third, the attenuation of loss that occurs if the direction in which the farmer adjusts is toward the optimum.

Minimization of $L$ is accomplished by taking first-order conditions with respect to $y_{t+\tau}$, which results in the following second-order difference equation:

$$\rho \left(y_{t+\tau+1} - \varphi_2 y^*_{t+\tau+1}\right) - \left(1 + \rho + \varphi_1\right)\left(y_{t+\tau} - \varphi_2 y^*_{t+\tau}\right) + \left(y_{t+\tau-1} - \varphi_2 y^*_{t+\tau+1}\right) = \varphi_1 \left(\varphi_2 - 1\right) y^*_{t+\tau} \tag{A2}$$

The solution to Equation A2 is the farmer's optimal policy. Nichell (1985) shows that when $\varphi_2$=0 the result is a partial adjustment rule in which the difference in yield from one period to the next is a fraction $\Theta$ of the gap between the actual and optimal levels of yield in the previous period:

$$y_t - y_{t-1} = \Theta\left[y_{t-1} - y^*_t\right] \tag{A3}$$

As $\Theta \rightarrow 1$ the farmer approaches instantaneous full adjustment. In general, $y^*_t$ represents a *moving* target which is latent and unobserved by the econometrician. Nichell (1985) investigates a range of plausible stylized representations of its law of motion, including a random walk with drift:

$$y^*_{t+\tau} = \Gamma_0 + y^*_{t+\tau-1} \tag{A4a}$$

and a second-order autoregressive model with a unit root:

$$y^*_{t+\tau} = \Gamma_0 + \Gamma_1 y^*_{t+\tau-1} + \Gamma_2 y^*_{t+\tau-2} \tag{A4b}$$

In both cases the solution to Equation A2 is an autoregressive distributed lag (ARDL) specification:

$$y_t = \Lambda_0 + \Lambda_1 y^*_t + \Lambda_2 y_{t-1} + \Lambda_3 y^*_{t-1} \tag{A5}$$

which in turn can be recast in the error correction model (ECM) form:

$$\Delta y_t = \Omega_0 + \Omega_1 \Delta y_t^* + \Omega_2 \left[ y_{t-1} - y_{t-1}^* \right] \tag{A6}$$

This is the basis for our empirical approach.

Equation ]refeqA6 elucidates how a simple long-run response can combine with contemporaneous random shocks to generate realistic yield series. For simplicity, suppose that target yield is related to a vector of exogenous predictor variables, $z$, by the linear relationship:

$$y_t^* = \boldsymbol{z}_t \boldsymbol{\Upsilon} \tag{A7}$$

in which $\boldsymbol{\Upsilon}$ denotes a vector of coefficients. At the end of periods $t$-1 and $t$, the subsequent harvests expected yield is given by:

$$\mathbb{E}_{t-1} y_t = \Omega_0 + \Omega_2 \left( \mathbb{E}_{t-1} \boldsymbol{z}_t - \boldsymbol{z}_{t-1} \right) \boldsymbol{\Upsilon} + \Omega_3 \left( y_{t-1} - \boldsymbol{z}_{t-1} \boldsymbol{\Upsilon} \right) \tag{A8a}$$

$$\mathbb{E}_t y_{t+1} = \Omega_0 + \Omega_2 \left( \mathbb{E}_t \boldsymbol{z}_{t+1} - \boldsymbol{z}_t \right) \boldsymbol{\Upsilon} + \Omega_3 \left( y_t - \boldsymbol{z}_t \boldsymbol{\Upsilon} \right) \tag{A8b}$$

It is customary to model farmers expectations as rational, in the sense that on average their guesses about the future are accurate and not systematically biased. Under this assumption, $\mathbb{E}_{\tau-1}$ $y_\tau$ = $y_\tau$ and $\mathbb{E}_{\tau-1}$ $\boldsymbol{z}_\tau$ = $\overline{\boldsymbol{z}}$, which is the long-run average value of the predictors (e.g., climate). Then, at $t$, subsequent yield is a function of observed past yield, predictors variables' long-run average, and their current interannual variability:

$$y_{t+1} = 2\Omega_0 \left(1 + \Omega_2\right) + \left(1 + \Omega_2\right)^2 y_{t-1} + 2\Omega_1 \left(1 + \Omega_2\right) \overline{\boldsymbol{z}} \boldsymbol{\Upsilon} - \left(\Omega_1 + \Omega_2 \Omega_3\right) \Delta \boldsymbol{z}_t \boldsymbol{\Upsilon} \tag{A9}$$

$$- \left(\Omega_1 + \Omega_2 \Omega_3\right) \left(2 + \Omega_2\right) \boldsymbol{z}_{t-1} \boldsymbol{\Upsilon}$$

## APPENDIX B: Econometric Strategy

Using the nomenclature in the main text, the standard empirical modeling approach is to estimate a static fixed effects regression model that identifies the effect of weather shocks' impact from their contemporaneous covariation with yield (Schlenker and Roberts, 2009; Ortiz-Bobea *et al.*, 2013; Tack *et al.*, 2015):

$$y_{c,t} = \tilde{\tilde{\alpha}}_c + \sum_g \left\{ \sum_j \tilde{\tilde{\eta}}^T_{j,g} \xi^T_{j,g,c,t} + \sum_k \tilde{\tilde{\eta}}^P_{k,g} \xi^P_{k,g,c,t} + \sum_l \tilde{\tilde{\eta}}^S_{l,g} \xi^S_{l,g,c,t} \right\} + \boldsymbol{X}_{c,t} \tilde{\tilde{\boldsymbol{\lambda}}} + \tilde{\tilde{u}}_{c,t} \tag{B1}$$

where a double tilde over a parameter identifies it as a static estimator, $\tilde{\tilde{\alpha}}$ denotes county fixed effects and $\tilde{\tilde{u}}$ is the corresponding static error term. The substantial temporal persistence exhibited by yields over the last half-century is symptomatic of year-to-year adjustment of farmers' management decisions to weather shocks—as anticipated by Equation A3 above. The key concern is that failure to capture this adjustment might bias estimates of the effects of yields of long-run meteorological changes associated with shifts in the climate, as the parameters in Equation B1 represent a mix of short- and long-run responses. Taking differences of Equation B1 over long periods, Burke and Emerick (2015) demonstrate persistent adverse impacts of extreme heat, raising questions as to whether farmers long-run adaptations to climate change will be sufficient to sustain yields. A common way of introducing dynamics explicitly is via an ARDL specification that includes lags of both the dependent and independent variables, e.g.

$$y_{c,t} = \alpha_c + \omega y_{c,t-1} + \sum_g \left\{ \sum_j \beta^T_{j,g} \xi^T_{j,g,c,t} + \sum_k \beta^P_{k,g} \xi^P_{k,g,c,t} + \sum_l \beta^S_{l,g} \xi^S_{l,g,c,t} \right\} + \boldsymbol{X}_{c,t} \boldsymbol{\gamma} + u_{c,t} \tag{B2}$$

Taking Equation B2 directly to the data generally results in biased and inconsistent estimates because of collinearity between the lagged dependent variable and the fixed effects (Nickell, 1981) but in the long time domain panels used by Schlenker and Roberts (2009); Ortiz-Bobea and Just (2012) and this study, the bias is likely to be small. The equivalence of Equations B2 and A5 can be exploited to rearrange the former into an ECM, with the analogue of Equation A7 given by

$$y^*_c = \sum_g \left\{ \sum_j \eta^T_{j,g} \xi^T_{j,g,c} + \sum_k \eta^P_{k,g} \xi^P_{k,g,c} + \sum_l \eta^S_{l,g} \xi^S_{l,g,c} \right\} + \boldsymbol{X}_c \boldsymbol{\lambda}$$

The result is Equation 1 in the text, in which short-run responses are identified from interannual variation and long-run responses are identified from from the covariation between lagged variables. The parameters of Equations 1 and refeqB2 are related by $\theta = \omega - 1$, $\boldsymbol{\eta}^v = (\boldsymbol{\beta}^v - \boldsymbol{\delta}^v)/(1-\omega)$ and $\lambda = (\boldsymbol{\gamma} - \boldsymbol{\zeta})/(1-\omega)$. The fixed effects account for unobserved factors that determine the average growth rate of yields over the sample period. Similar to Equation A3 and A6, the term in square braces is the instantaneous yield gap—the divergence between the realization of yield at the prior harvest and producers' equilibrium expectations of the long-run climatically-determined level of yield. Intuitively, if weather remained unchanged from the previous year (i.e., all the $\Delta\xi^T = \Delta\xi^P = \Delta\xi^S = 0$), the change in yield relative to the previous year would be a fraction $\theta \in (0,1)$ of the current yield gap, generated by farmers' adjustments that are not directly observed. However, weather is not constant, and this exerts an additional short-run influence on the interannual change in yield. The ECM thus captures the way in which past yield, climate, and weather-driven deviations from equilibrium target yield drive the historical evolution of county yield series, similar to Equation A9. The caveat is that this benefit comes at the cost of inability to incorporate secular count $x$ year effects to control for the influence of unobserved shocks that are both localized and time-varying (e.g., changes in land prices), which Deschênes and Greenstone (2012) find to be central to the significance of temperature's influence.

## APPENDIX C: Data

Historical Production and Harvested Area: We obtained annual county-level production and harvested area over the period 1948-2010 for corn, wheat, soybeans, sorghum and cotton from the US Dept. of Agriculture Quickstats database. There are numerous limitations to these data. Crucially, they do not consistently distinguish irrigated and rainfed production by county, but rather tabulate the total the acreage and production under both management regimes. Also, historical wheat production series combine winter and spring wheat.

Historical Weather Exposure: weather inputs to our empirical analysis are calculated from the Global Land Data Assimilation System (GLDAS) forcing files of 3-hourly assimilated temperature and precipitation observations, and simulated soil moisture, all on a 1° grid (Rodell *et al.*, 2004). These variables were bilinearly interpolated to US county boundaries and counts of 3-hour exposure were accumulated over each annual growing season, which for simplicity we assume is represented by the fixed 7-month window April-October. To capture potentially large shifts in the effects of heat and moisture with different crop growth stages, we split the growing season into sub-periods of equal length (day of year 90-197 and 198-305). For each stage within a county-year pair we compute the counts of 3-hour observations that fall within intervals of temperature, precipitation and soil moisture. For example, given a 3-hourly temperature time series for county $c$ in year $t$, subset to sub-period $g$, $\boldsymbol{T}_{c,t}\langle g \rangle$, the corresponding covariate for the $j^{th}$ temperature interval with support $\left(\underline{T}_j, \overline{T}^j\right)$ is given by $\xi^T_{j,g,c,t} = N\left[\underline{T}_j < \boldsymbol{T}_{c,t} < \overline{T}^j\right]$, where $N$ is the count of observations meeting the interval's criteria.

Statistical controls: Consistent annual data series of county characteristics were not available for the long time-horizon of our sample. We were able to construct a single control over this period: an index of potential irrigation. Our dependent variable is an average of irrigated and non-irrigated yields, which raises the possibility of bias of unknown magnitude in our estimates relative to the true impact of meteorology. Furthermore, our ability to control statistically for irrigation is hampered by paucity of historical data on crop water applications. Following Hansen *et al.* (2011, 2014), our solution is to treat irrigation as a latent variable whose yield impact is inferred from the partial covariation between yields and irrigation potential. Data on irrigation infrastructure are collected from the US Army Corps of Engineers' National Inventory of Dams (NID), which records facilities' location, primary purpose, storage capacity and in-service dates. We restrict our attention to dams whose primary purpose is listed as irrigation, and assign the storage of each facility to the county in which it is located for all years subsequent to its date of construction. Cross-county and year-on-year differences in dam capacity additions generate an infrastructure series that exhibits substantial spatial and temporal variation. Our annual irrigation variable is constructed by interacting each county's dam capacity with each year's accumulated January-October precipitation. The result is an indicator of a county's cumulative quantity of water that is stored and potentially available for application to crops locally over the course of each year's growing season.

## APPENDIX D: Crop Impact Projections

In a perfect world, yield responses to meteorology under irrigated and rainfed management regimes are statistically identified using separate instances of Equation 1:

$$\Delta y_{c,t} = \mu_c^m + \sum_g \left\{ \sum_j \beta_{j,g}^{T,m} \Delta\xi_{j,g,c,t}^T + \sum_k \beta_{k,g}^{P,m} \Delta\xi_{k,g,c,t}^P + \sum_l \beta_{l,g}^S \Delta\xi_{l,g,c,t}^{S,m} \right\} + \Delta \boldsymbol{X}_{c,t} \boldsymbol{\gamma}^m \quad \text{(D1)}$$

$$+\theta^m \left[ y_{c,t-1}^m - \sum_g \left\{ \sum_j \eta_{j,g}^{T,m} \xi_{j,g,c,t-1}^T + \sum_k \eta_{k,g}^{P,m} \xi_{k,g,c,t-1}^P + \sum_l \eta_{l,g}^{S,m} \xi_{l,g,c,t-1}^S \right\} + \boldsymbol{X}_{c,t-1} \boldsymbol{\lambda^m} \right] + \varepsilon_{c,t}^m$$

However, the crucial limitation of our dataset is we only have consistent historical county-level series of average yields, which are calculated from the sums of irrigated and rainfed crop output and acreage:

$$Y_{c,t} = \left(Q_{c,t}^I + Q_{c,t}^R\right) / \left(H_{c,t}^I + H_{c,t}^R\right) \quad \text{(D2)}$$

The dependent variable in Equation 1 is therefore:

$$\Delta y_{c,t} = \Delta \log\left(Q_{c,t}^I + Q_{c,t}^R\right) - \Delta \log\left(H_{c,t}^I + H_{c,t}^R\right) \quad \text{(D3)}$$

which, by the property of the logarithmic differential can be restated:

$$\Delta y_{c,t} \approx \phi_{c,t}^{I,Q} \Delta \log Q_{c,t}^I + \phi_{c,t}^{R,Q} \Delta \log Q_{c,t}^R - \phi_{c,t}^{I,H} \Delta \log H_{c,t}^I - \phi_{c,t}^{R,H} \Delta \log H_{c,t}^R \quad \text{(D4)}$$

where $\phi_{c,t}^{m,Q}$ and $\phi_{c,t}^{m,H}$ are the instantaneous fractions of total output and harvested area attributable to cultivation under regime $m$.

In principle the regime-specific parameters ($\boldsymbol{\eta}^{v,m}$) are identified if we make two key assumptions. The first is that for a given crop in each county, the divergence between the instantaneous fractions of output and acreage in each management regime is not "too" large, allows us to replace the weights in Equation A6 with average fractions for the $I$ and $R$ terms: $\phi_{c,t}^{v,Q} \approx \phi_{c,t}^{v,H} \approx \phi_{c,t}^v$ where $\phi_{c,t}^I + \phi_{c,t}^R = 1$. The first difference of average yield is then the weighted sum of irrigated and rainfed components:

$$\Delta y_{c,t} \approx \phi_{c,t}^I \left(\Delta \log Q_{c,t}^I + \Delta \log H_{c,t}^I\right) + \phi_{c,t}^R \left(\Delta \log Q_{c,t}^R - \Delta \log H_{c,t}^R\right) = \phi_{c,t}^I \Delta y_{c,t}^I + \phi_{c,t}^R \Delta y_{c,t}^R \quad \text{(D5)}$$

The second assumption is that irrigated and rainfed producers' adjust to equilibrium at similar rates ($\theta^I \approx \theta^R \approx \theta$). Then, substituting Equation A3 into Equation A7, the long-run terms in Equation 1 can be decomposed as:

$$\eta_{j,g}^T \xi_{j,g,c,t-1}^T = \phi_{c,t}^I \eta_{j,g}^{T,I} \xi_{j,g,c,t-1}^T + \phi_{c,t}^R \eta_{j,g}^{T,R} \xi_{j,g,c,t-1}^T \quad \text{(D6a)}$$

$$\eta_{k,g}^P \xi_{k,g,c,t-1}^P = \phi_{c,t}^I \eta_{k,g}^{P,I} \xi_{k,g,c,t-1}^P + \phi_{c,t}^R \eta_{k,g}^{P,R} \xi_{k,g,c,t-1}^P \quad \text{(D6b)}$$

$$\eta_{l,g}^S \xi_{l,g,c,t-1}^S = \phi_{c,t}^I \eta_{l,g}^{S,I} \xi_{l,g,c,t-1}^S + \phi_{c,t}^R \eta_{l,g}^{S,R} \xi_{l,g,c,t-1}^S \quad \text{(D6c)}$$

However, data constraints pose an insurmountable obstacle to direct operationalization of Equation D3. Comprehensive geographic coverage of the distribution of irrigated and rainfed cultivation is available only circa year 2000 (MIRCA), generating observed weights ($\phi_{c,t}^I$ and $\phi_{c,t}^R$) that lack the temporal variation necessary for identification. Consequently we retain specification of Equation 1 for our empirical model. The foregoing analysis nonetheless has important implications for construction of yield projections. If we assume the limiting case of perfect crop water application that completely shields irrigated production from water stress, then in Equation D1 precipitation and soil moisture are unlikely to exert significant long-run effects on irrigated yields independent of the driving force of irrigation capacity. We may therefore attribute eq. (1)'s composite precipitation and soil moisture responses entirely to rainfed production: $\eta_{k,g}^{P,R} \approx \eta_{k,g}^{P}$, $\eta_{l,g}^{S,R} \approx \eta_{l,g}^{S}$ and $\eta_{k,g}^{P,R} = \eta_{l,g}^{S,R} = 0$, while treating rainfed and irrigated crops' orthogonal temperature responses as statistically indistinguishable: $\eta_{j,g}^{T,I} = \eta_{j,g}^{T,R} = \eta_{j,g}^{T}$. This partitioning motivates our impact response functions Equations 2 and 3.

Crop yield responses to $CO_2$ concentrations are highly uncertain. Our impacts are estimated based on rates of yield response to doubled $CO_2$ ($FR_i^{2\times CO_2}$) summarized by (Hatfield *et al.*, 2011, Table 1). To capture the progressive saturation of yield increases with increasing $CO_2$, we specify crop-specific logarithmic functions that use as a base value the 1980–2010 average $CO_2$ concentration (370 ppm):

$$F_i^m = 1 + \kappa_i^m \cdot FR_i^{2\times CO_2} \cdot (\log C - \log 370) \,/\, \log 2 \tag{D7}$$

Our calibration also incorporates current understanding of the CFE's dependence on moisture stress. We assume that the fertilization rates in Hatfield *et al.* (2011) are typical of rainfed crops experiencing moderate drought stress, which corresponds to an average growing season precipitation-potential evapotranspiration ratio (P/PET) of 0.5, while irrigated crops are treated as unstressed (P/PET $\geq$ 1) and, consequently, subject to smaller improvements in yield. This differential is captured by the scaling parameter $\kappa_i^m$, whose value is unity ($<$1) for rainfed (irrigated) crops. We model the attenuation of yield benefits with irrigation as the ratio of the CFE under wet conditions to that under dry conditions, using crop-specific estimates from (McGrath and Lobell, 2013, Table 3). The parameters of Equation D7 are summarized in Table D1.

**Table D1.** Parameterization of the $CO_2$ fertilization effect.

| | **Fractional increase in rainfed yields with doubled $CO_2$ ($FR_i^{2\times CO_2}$)** | **Ratio of irrigated to rainfed yield response ($\kappa_i^I$)** |
|---|---|---|
| Corn | 0.04 | 0.063 |
| Sorghum | 0.08 | -0.1863 |
| Cotton | 0.44 | 0.4462* |
| Soybeans | 0.36 | 0.4462 |
| Wheat | 0.31 | 0.1707 |

* Assumed identical to soybeans.

The implications of Equation A9 for the CFE in the paper are shown in Figure D1. Our calibrated CFE response functions are in generally good agreement with the FACE experiments and Amthor *et al.* (2001), but are systematically smaller than the responses for corn and sorghum assumed by global gridded crop models.

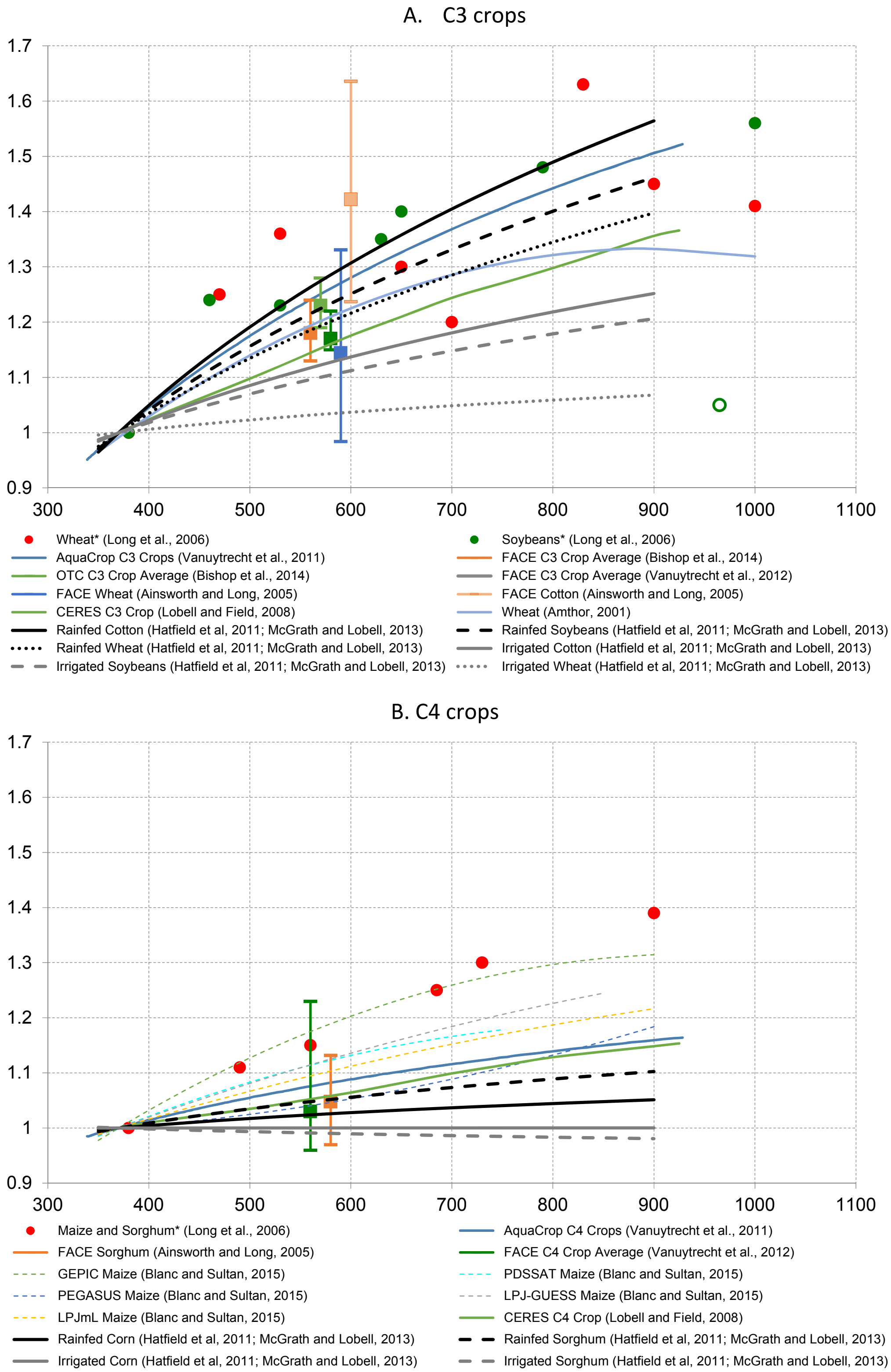


**Figure D1.** The $CO_2$ fertilization effect: comparison of our approach with the literature. * indicate estimates from chamber studies.

## APPENDIX E: Additional Results

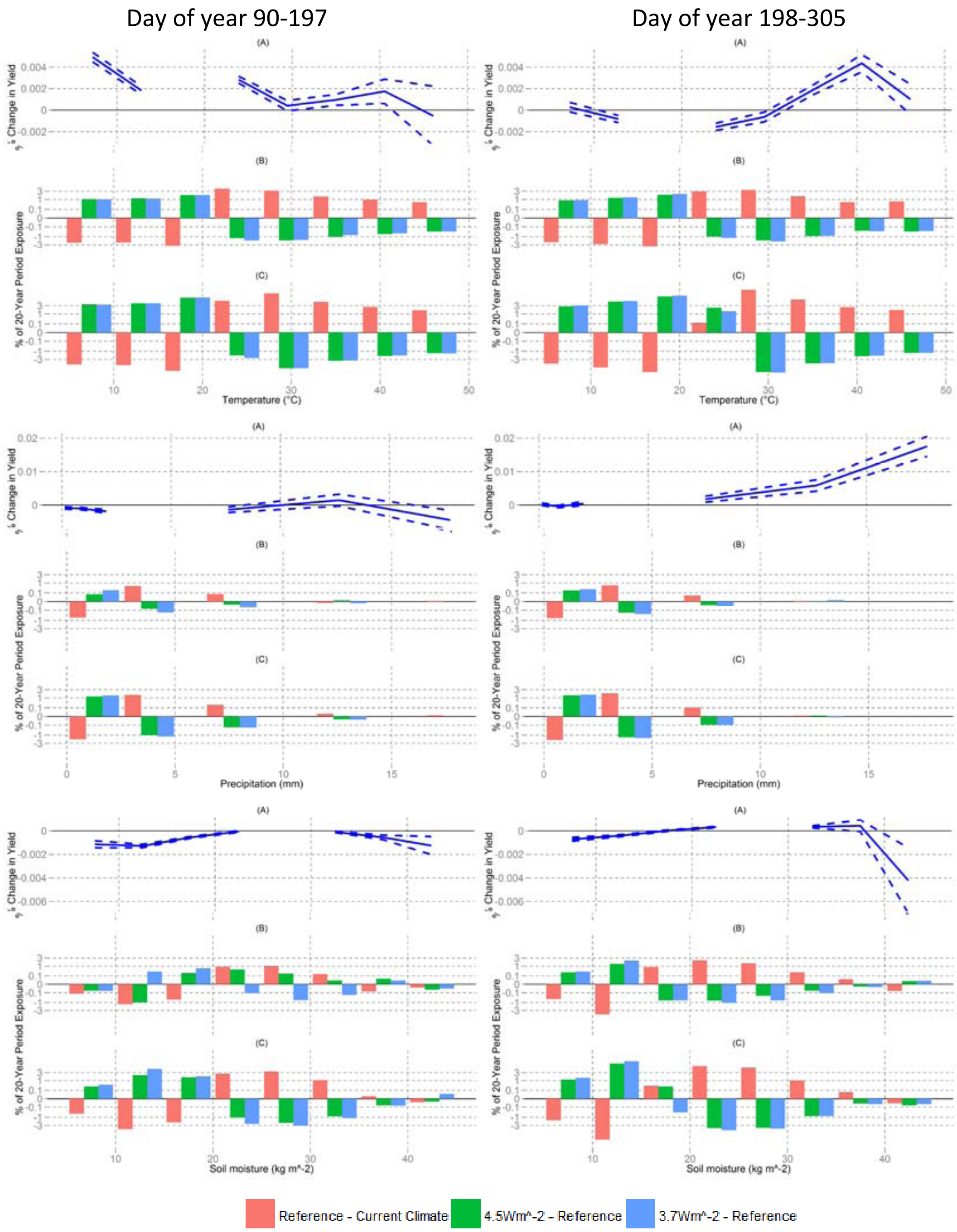


**Figure E2.** Wheat empirical yield response functions (A) and the change in the distributions of average county temperature, precipitation and soil moisture circa year 2050 (B) and 2100 (C), over growing season sub-periods. Gaps in splines correspond to omitted modal intervals. Histograms show the differences in the distributions of exposure between the no-policy reference scenario and the current climate, and between the 4.5 $W\,m^{-2}$ and 3.7 $W\,m^{-2}$ GHG mitigation scenarios and the reference case.

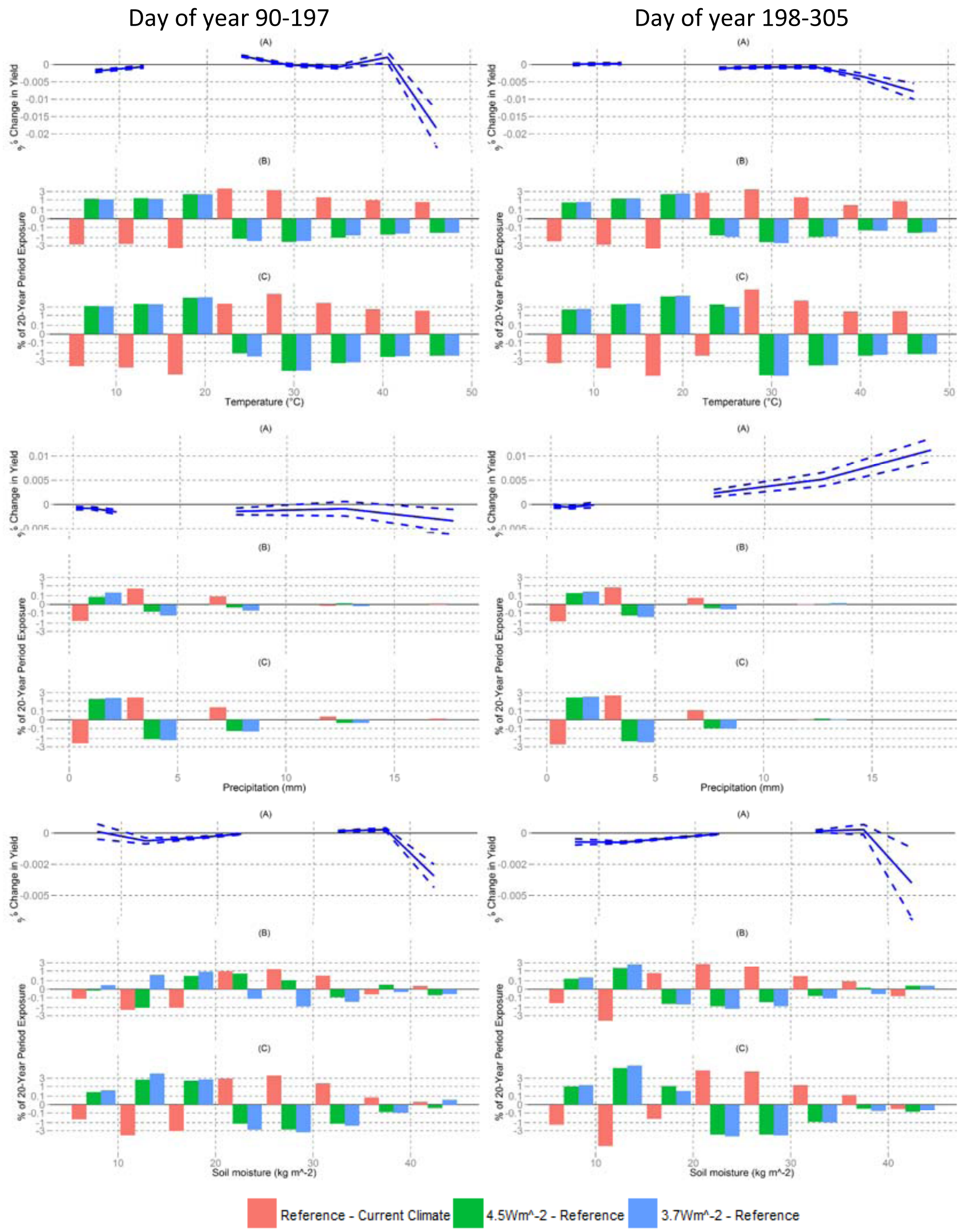


**Figure E3.** Soybean empirical yield response functions (A) and the change in the distributions of average county temperature, precipitation and soil moisture circa year 2050 (B) and 2100 (C), over growing season sub-periods. Gaps in splines correspond to omitted modal intervals. Histograms show the differences in the distributions of exposure between the no-policy reference scenario and the current climate, and between the 4.5 W m$^{-2}$ and 3.7 W m$^{-2}$ GHG mitigation scenarios and the reference case.

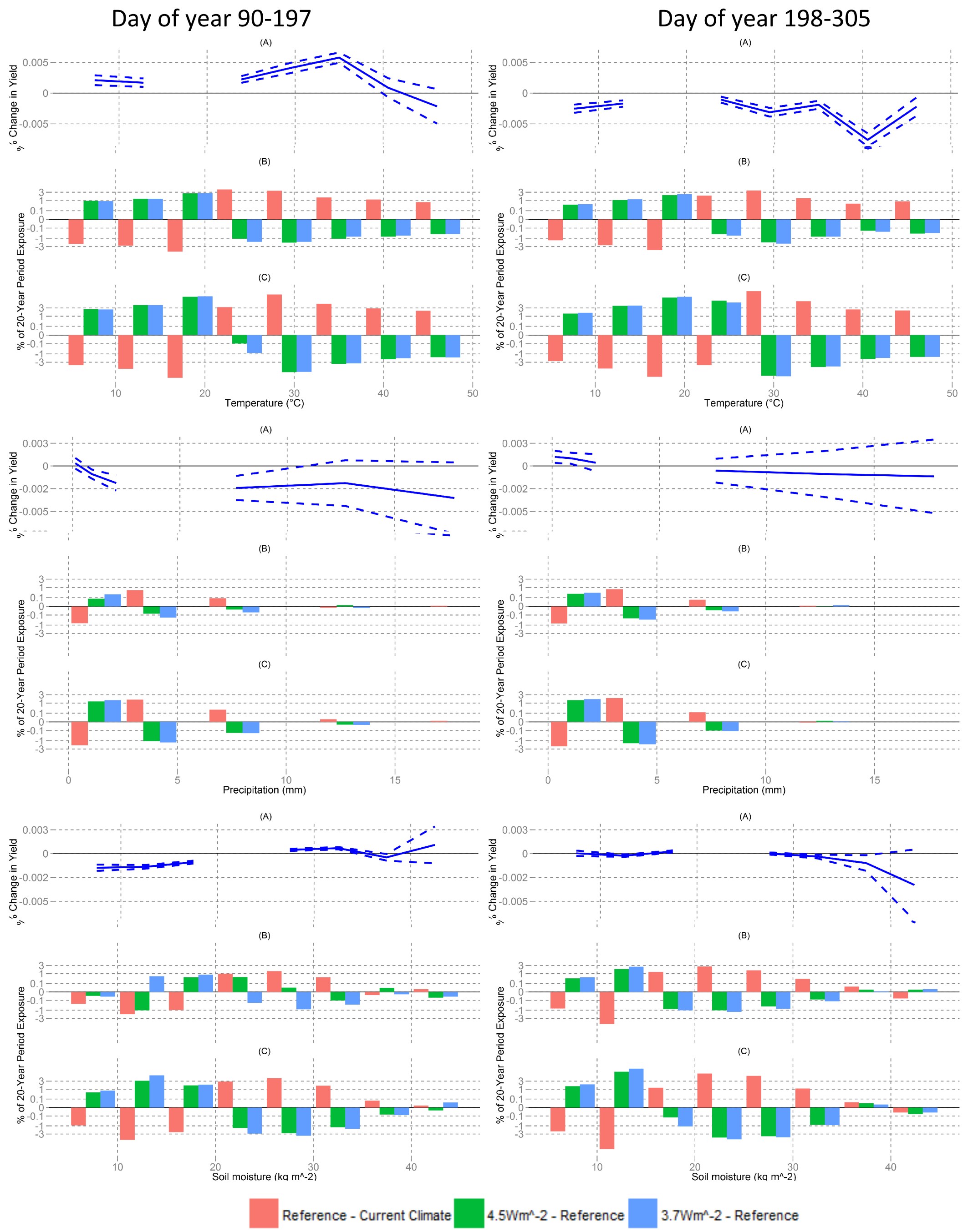


**Figure E4.** Sorghum empirical yield response functions (A) and the change in the distributions of average county temperature, precipitation and soil moisture circa year 2050 (B) and 2100 (C), over growing season sub-periods. Gaps in splines correspond to omitted modal intervals. Histograms show the differences in the distributions of exposure between the no-policy reference scenario and the current climate, and between the $4.5\,\mathrm{W\,m^{-2}}$ and $3.7\,\mathrm{W\,m^{-2}}$ GHG mitigation scenarios and the reference case.

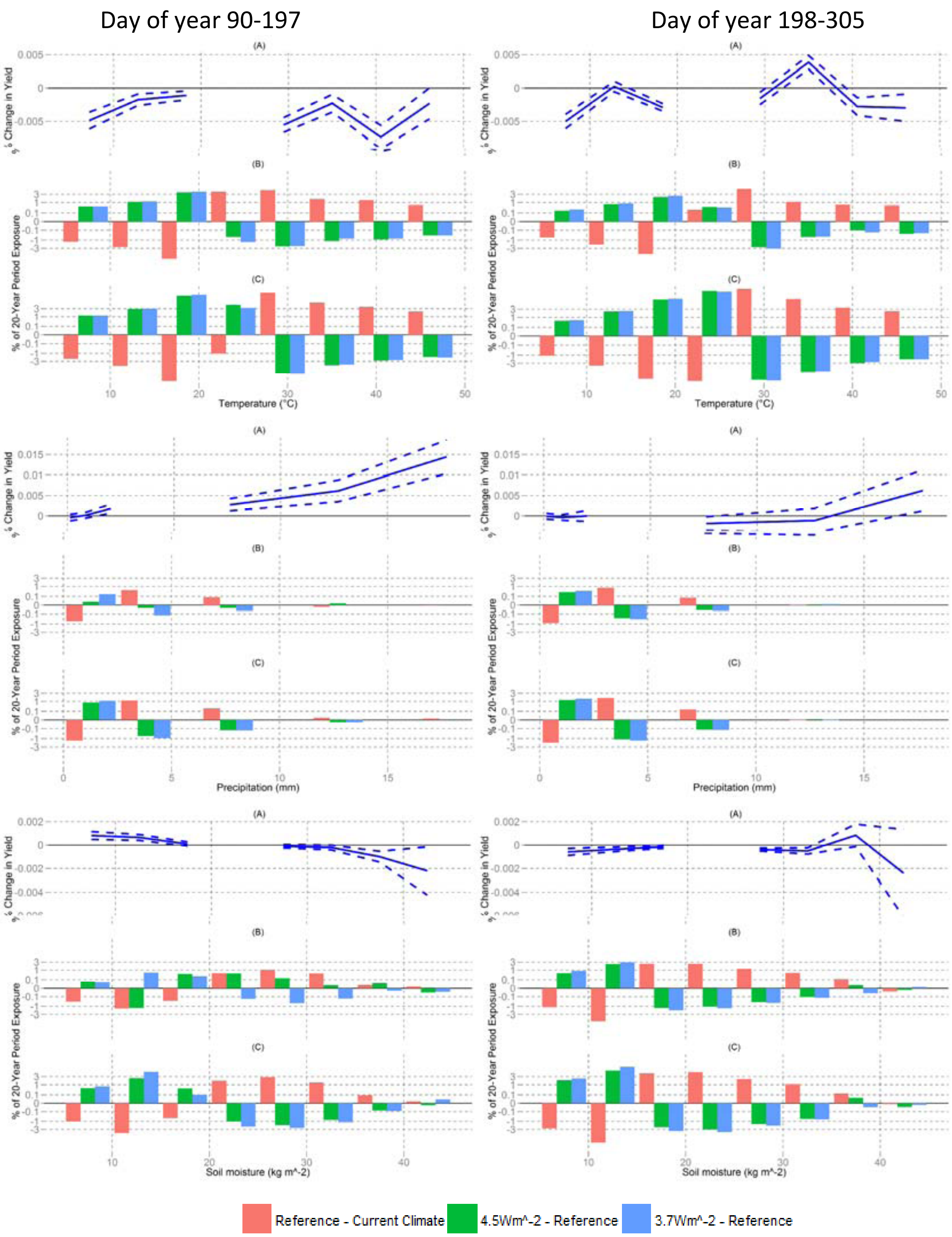


**Figure E5.** Cotton empirical yield response functions (A) and the change in the distributions of average county temperature, precipitation and soil moisture circa year 2050 (B) and 2100 (C), over growing season sub-periods. Gaps in splines correspond to omitted modal intervals. Histograms show the differences in the distributions of exposure between the no-policy reference scenario and the current climate, and between the 4.5 $\mathrm{W\,m^{-2}}$ and 3.7 $\mathrm{W\,m^{-2}}$ GHG mitigation scenarios and the reference case.

**Table E1.** Aggregate annual changes in crop yields, production and associated gross costs and benefits relative to current climate in the no-policy reference scenario, and aggregate avoided changes in crop yields and associated costs and benefits under GHG mitigation scenarios, circa years 2050 and 2100, assuming no $CO_2$ fertilization effect. (A) aggregate yield changes; (B) prices and quantities in current agricultural system; (C) prices and quantities scaled according to future growth simulated by the MIT-EPPA model's CIRA simulations.

| | 2036-2055 | | | 2086-2115 | | |
|---|---|---|---|---|---|---|
| | Ref | 4.5 $Wm^{-2}$ | 3.7 $Wm^{-2}$ | Ref | 4.5 $Wm^{-2}$ | 3.7 $Wm^{-2}$ |
| | A. Average Change in Yield Relative to Current Climate (%) | | | | | |
| Wheat | -4.1 | -0.7 | -1.2 | -9.2 | -1.9 | -2.4 |
| Soybeans | -5.9 | 0.3 | -1.0 | -14.8 | -2.3 | -2.6 |
| Sorghum | 5.6 | 2.3 | 2.0 | 15.3 | 4.4 | 1.1 |
| Cotton | -2.2 | 0.5 | 0.0 | -11.0 | -0.4 | -1.4 |
| Corn | 5.9 | 5.0 | 4.5 | 9.3 | 6.2 | 3.5 |
| | B. Current Agricultural System | | | | | |
| | (i) Average Change in Production Relative to Current Climate ($10^6$ tons) | | | | | |
| Wheat | -2.6 | -0.5 | -0.8 | -5.7 | -1.2 | -1.5 |
| Soybeans | -3.9 | 0.2 | -0.6 | -9.8 | -1.5 | -1.8 |
| Sorghum | 0.9 | 0.4 | 0.3 | 2.5 | 0.7 | 0.2 |
| Cotton | -0.1 | 0.0 | 0.0 | -0.4 | 0.0 | -0.1 |
| Corn | 13.7 | 11.5 | 10.3 | 21.5 | 14.3 | 8.0 |
| | (ii) Impact Gross Cost (negative) or Benefit (positive) in Reference Scenario; Mitigation Net Benefit (positive) or Cost (negative) in Policy Scenarios (2010 $ M) | | | | | |
| Wheat | -464 | 383 | 327 | -1028 | 818 | 764 |
| Soybeans | -1218 | 1275 | 1020 | -3048 | 2574 | 2504 |
| Sorghum | 88 | -52 | -57 | 244 | -173 | -226 |
| Cotton | -136 | 169 | 134 | -685 | 657 | 599 |
| Corn | 1378 | -213 | -334 | 2166 | -727 | -1360 |
| **Total** | **-352** | **1562** | **1089** | **-2351** | **3149** | **2281** |
| | C. Projected Future Agricultural System | | | | | |
| | (i) Average Change in Production ($10^6$ tons) | | | | | |
| Wheat | -6.5 | -1.1 | -1.7 | -37.5 | -6.6 | -7.2 |
| Soybeans | -10.0 | 0.4 | -1.4 | -65.0 | -10.1 | -11.6 |
| Sorghum | 2.3 | 0.9 | 0.7 | 16.5 | 4.8 | 1.2 |
| Cotton | -0.2 | 0.0 | 0.0 | -1.0 | 0.0 | -0.1 |
| Corn | 34.8 | 27.5 | 23.1 | 141.6 | 94.1 | 52.7 |
| | (ii) Impact Gross Cost (negative) or Benefit (positive) in Reference Scenario; Mitigation Net Benefit (positive) or Cost (negative) in Policy Scenarios (2010 $ M) | | | | | |
| Wheat | -1473 | 1255 | 1128 | -9730 | 8197 | 8544 |
| Soybeans | -3863 | 4114 | 3426 | -28860 | 24935 | 25775 |
| Sorghum | 280 | -174 | -200 | 2306 | -1678 | -2330 |
| Cotton | -433 | 540 | 440 | -2508 | 2467 | 2425 |
| Corn | 4372 | -931 | -1518 | 20508 | -7043 | -13998 |
| **Total** | **-1116** | **4804** | **3276** | **-18285** | **26878** | **20416** |

**Table E2.** Prior Estimates of Climate Change Impacts on US Agriculture. Note that none of these studies takes into account the effect of $CO_2$ fertilization.

| Study | Impact Endpoint | Empirical Approach | Climate Change Scenarios | Impact Magnitude |
|---|---|---|---|---|
| Mendelsohn et al (1994) | County agricultural land values per acre | Hedonic regression on cross-sectional data | 5°F temperature increase,<br><br>8% precipitation increase,<br><br>uniform by region and season | Cropland weights: $8 B (1982) annualized<br><br>Crop revenue weights: $2 B (1982) annualized |
| Schlenker et al (2006) | County value of land and buildings per acre for counties east of 100th meridian | Hedonic regression on panel data | HadCM3 runs of 4 SRES scenarios, 2020-2049 and 2070-2099 | $3.1 B to $7.2 B (1997) annually, 2020-2049<br><br>Comparable impacts for 2070-2099 not reported |
| Deschenes and Greenstone (2007) | County agricultural profits per acre<br><br>County corn and soybean yields | Regression on panel data | Hadley II run of 1% per year $CO_2$ increase with IS92A aerosol forcing, 2070-2099 | -$0.5 B to $3.1 B (2002) reduction in profit<br><br>-0.02 B to 0.05 B bushel reduction in corn and soybean output |
| Fisher et al (2012) | | | Hadley II-IS92A used in Deschenes and Geenstone (2007)<br><br>Hadley III-B2 scenario | 37% to 55% reduction in profit<br><br>11% to 42% reduction corn yield<br><br>16% to 52% reduction soybean yield |
| Deschenes and Greenstone (2012) | | | Hadley II-IS92A used in Deschenes and Geenstone (2007)<br><br>CCSM run of A2 scenario, 2070-2099 | -$0.2 B to $14.8 B (2002) annually |
| Schlenker and Roberts (2009) | Corn, soybean and cotton yields for counties east of 100th meridian | Regression on panel data | HadCM3 runs of 4 SRES scenarios, 2020-2049 and 2070-2099 | 18% to 30% reduction in aggregate yield, 2020-2049<br><br>30% to 80% reduction in aggregate yield, 2070-2099 |
| Ortiz-Bobea (2013) | Corn yields in 90 irrigated and 800 non-irrigated counties | Regression on panel data | HadGEM2 runs of RCP 2.6, 6 and 8.5 scenarios, 2039-2059 and 2079-2099 | -6% to 13% reduction in aggregate yield, 2039-2059<br><br>-3% to 31% reduction in aggregate yield, 2079-2099 |
| Burke and Emerick (2015) | Corn and soybean yields for counties east of 100th | Long differences regression on | 18 ESM runs of A1B scenario, 2050 | 15% median (8% min, 62% max) reduction in |

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