Future climate impacts on global agricultural yields over the 21st century

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Abstract

Analyses of the future impacts of changing crop yields on agricultural production, prices, food security, and GDP growth using Integrated Assessment models require country-level yield shocks due to changing weather conditions, for a wide range of crops and warming scenarios. We characterize impacts of different climate futures on crop yields for individual countries and years. We use historical crop yield and weather data to empirically estimate annual crop yield responses to temperature and precipitation, constructing reduced-form statistical models that are then coupled with earth system model outputs for the same variables to project future yields. Our main result is a panel of annual shocks to yields of 12 crops (cassava, cotton, maize, potatoes, rice, sorghum, soybean, sugar beet, sugarcane, sunflower, and winter and spring wheat) for 58–136 countries, depending on the crop, through 2099, under moderate and vigorous warming scenarios. We find that global yield impacts by century’s end (2086–2095) are −2%, −19%, −14%, and −1%, without the CO2 fertilization effect (CFE), for maize, rice, soybean, and wheat, respectively, with similar global values with CFE. However, the global and decadal averages mask regional and year-to-year differences that may have large economic consequences, which IAMs could more fully address by representing agricultural yield impacts through the parameters supplied by our study.

1. Introduction

Agricultural systems’ vulnerability to changing climate conditions has the potential to lead to widespread risks to social, environmental, and economic outcomes such as agricultural commodity supplies, food security, and growth in Gross Domestic Product (GDP). Agricultural markets are globally-integrated and feedback to energy, water, and labor markets. Thus, analysis of the implications of changing climate conditions on these outcomes requires Integrated Assessment (IA) modeling, which is global in coverage and links socioeconomic, land, water, energy, and climate systems. Recognition of the importance and vulnerability of agricultural systems to future changes in the climate has stimulated a substantial literature exploring agricultural climate impacts (IPCC 2014a, b) and economic analyses of these impacts using IA models (Nelson et al 2014a, 2014b, Baker et al 2018).

Much of the literature on both the impacts of climate on crop yields (Lobell and Field 2007, Rosenzweig et al 2014) and the economic and land use implications (Schmitz et al 2013, Nelson et al 2014a, Baker et al 2018) has focused on long-term trends of changing climate on crop yields. But year-to-year changes in weather may have more pronounced affects than these longer-term changes. To
understand the role of interannual variability under changing climate conditions on economic outcomes, IA models require country-level projections of shocks to crop yields under a range of future weather and climate conditions.

The genesis of this paper was in the need to develop a comprehensive assessment of climate impacts on agriculture in Latin America and the Caribbean, within the Latin American Modeling Project (Waldhoff et al in review), using four IA models. To perform these experiments, IA models require projections of yield impacts for many crops and regions across multiple future climate scenarios, as analysis of regional climate-related agricultural impacts is inadequate without explicitly considering the climate impacts elsewhere in the world (Baker et al 2018). Thus, a consistent comparison of the broad economic consequences of climate impacts on crop yields requires a consistent, robust, validated, computationally efficient, globally comprehensive method for projecting crop yields at a country-level for many crops that could be used to generate projections of exogenous shocks to yields under multiple warming scenarios. Despite the voluminous literature, no such projections of agricultural climate impacts—annual impacts for multiple crops, at a country scale, under multiple Earth System Models’ (ESMs) realizations of different warming scenarios—could be found.

For this reason, both the empirical climate economics literature that has applied statistical modeling techniques and the agroecosystem process simulation literature employing Global Gridded Crop Models (GGCMs) have focused attention on the effects of meteorological and other climate variables on yields. Within this existing literature on climate impacts on crop yields, using both statistical (Lobell and Field 2007, Schlenker and Roberts 2009, Sue Wing et al 2015, Thomas 2015, Mistry et al 2017) and biophysical process-based (Rosenzweig et al 2014, Elliott et al 2015) models, there is a tension between higher fidelity analysis at fine spatial and temporal scales and the need for comprehensive global coverage for a wide range of crops. More finely scaled analyses, tuned for precise estimates under local conditions, lack the coverage required to drive IA models, while GGCMs’ broad geographic coverage makes them suited to assess the global impacts of climate change, the slate of crops they have been able to assess is limited by the necessity of calibrating their internal representations of crop growth to field conditions in a sufficiently broad range of climates (Müller et al 2017).

It is not straightforward to transparently link GGCMs’ simulated yields to shifts in fundamental climate variables (Mistry et al 2017), which are necessary to produce future yield impacts for multiple future climate scenarios. Recent work has suggested that GGCMs show crops to be more weather-sensitive that the historical record (Mistry et al 2017). Such attribution is the strength of empirical approaches, whose major result is reduced-form statistical response surfaces that capture the average dependence of yields on temperature, precipitation (Lobell et al 2007, Schlenker and Roberts 2009), and soil moisture (Ortiz-Bobea 2013). Yet, because many of these responses are derived using observations of yields and weather at fine spatial scales, the absence of similar datasets in large parts of the world limits their applicability to the global scale.

A further limitation is the difficulty of using observational datasets to statistically estimate the CO₂ fertilization effect (CFE). Because CO₂ is atmospherically well-mixed, its concentration acts as a common stimulus to agriculture in virtually all locations for a given annual growing season, and the steady increase in CO₂ concentrations results in collinearity between the CFE and variables whose effects accumulate over time, but which are rarely observed (e.g. intensification, improvements in technology and agricultural management practices).

To fill this gap in the literature, this paper develops an empirical characterization of climatically-driven risks of impacts to agriculture at the global scale that can be used to project annual exogenous shocks to crop yields due to changing weather conditions and CO₂ concentrations for 12 crops (cassava, cotton, maize, potatoes, rice, sorghum, soybean, sugar beet, sugarcane, sunflower, winter wheat, and spring wheat) at a national level. We then use the fitted models to project climate change impacts on yields through the end of the century, at a country and crop level, under three ESM simulations of future meteorology under two warming scenarios. The yield shocks that we estimate here are designed for use in IAM analyses of future climate impacts on crop yields; they can be aggregated to the requisite model region, time steps, and crop categories and applied within the models’ land productivity or exogenous assumptions of yield improvements to generate changes in yields. A unique contribution of this work is the production of series of annual shocks under different warming scenarios at country-levels for 12 crops, provided in online Supplementary Information (SI). However, these results are difficult to summarize and compare with prior literature, so in the main text we focus our

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6The regional and crop aggregations of the models range from five global regions with one representative agricultural commodity to 32 global regions with 13 crop commodities.

7Prior work has applied empirical approaches to meta-analysis datasets (Moore et al 2017) or GGCM simulated yields (Schauerger et al 2016, Mistry et al 2017) to compensate for these data gaps.

8(Sue Wing et al 2015) is an example of an empirical study that uses post-estimation calculations to account for the CFE’s influences on the yield impacts of future climate change.
discussion on ten-year average changes at global and regional spatial scales across multiple ESMs for maize and rice only. Understanding the potential economic implications of a changing climate on agriculture requires projections of yield shocks at both country and annual scales, as a 1 °C change in global average temperature implies different patterns of regional temperature and precipitation changes depending on the RCP and ESM scenario. These spatial patterns will have different implications for country-level production and the effects will also vary depending on interannual variability around these average changes.

2. Methods

2.1. Empirical modeling

The empirical analysis is conducted at a country scale, using monthly gridded average temperature and total precipitation aggregated to the national level, weighting by harvested area and using country-crop specific growing season calendars. This approach is similar in concept to (Lobell and Field 2007), but operating at a country, rather than global, scale. We chose this level of aggregation for two reasons. First, the historical data for both our dependent variable, yields, and a primary control variable, GDP/cap, are country-level averages.9 Using finer spatial temperature and precipitation data to predict average country-level yields would artificially increase the number of observations and introduce more uncertainty, as each grid cell would not have the same yields as the country average reported by the FAO. The weather data itself is also a source of uncertainty, as these are re-analysis data, rather than direct measurements. Second, this work was conducted primarily to produce series of projected yield shocks under different ESM and RCP scenarios that can be readily used in IA models to analyze the implications of future climate on global agriculture. These models generally operate at country to regional scales, with different regional definitions. Thus, country-level projections enable their use in multiple models. Finally, this approach is consistent with the finding of (Lobell and Burke 2010) that the performance of statistical models was improved when trained on aggregate country level data compared to site specific data.

The main data sources used in our empirical analysis are country-year series of yields of 12 crops from the United Nations Food and Agriculture Organization (FAO) (FAO 2018). GDP per capita from the Penn World Table (Feenstra et al 2015) for the period 1961–2016. Monthly average temperature and monthly total precipitation fields from the Water and Global Change (WATCH) 20th century forcing dataset for the period 1960–2001 (Weedon et al 2011).

For each crop, historical temperature and precipitation exposures were geographically aggregated to national scales using cropland weights from MIRCA2000 (Portmann et al 2010) in conjunction with national boundaries and restricted to a fixed sub-annual growing seasons defined by crop calendar dataset (Portmann et al 2010), supplemented by (Sacks et al 2010) for country-crop combinations unavailable in the former. From these calculations we derived the weather exposures used in our statistical model: the growing season minimum, mean, and maximum of temperature and precipitation for each crop in every country and year. The final dataset used to estimate historical yield responses to weather shocks is an unbalanced country-year panel for the period 1961–2001. Details of the construction of the dataset are provided in the SI. Sample sizes differ by crop, ranging from 1245 (winter wheat) to 5705 (maize) (see table S1).

Using our dataset, we estimated the following panel data econometric model:

\[
y_{i,t} = \mu_i + \lambda_t + \chi m_{i,t} + \beta_1 \frac{\text{Mean}}{\text{Max}} T_{i,t} + \beta_2 \frac{\text{Mean}}{\text{Max}} P_{i,t} + \gamma_1 \frac{\text{Min}}{\text{Max}} T_{i,t} + \gamma_2 \frac{\text{Min}}{\text{Max}} P_{i,t} + \delta_i + \epsilon_{i,t}.
\]

(1)

Here, i and t index countries and years, y and m are the natural logarithms of yield and per capita GDP, which acts as a proxy unobservable characteristics that are related to income, such as improved management practices; \(T^k\) and \(P^k\) with \(k \in \{\text{Mean}, \text{Min}, \text{Max}\}\) denote the mean, minimum, and maximum growing season monthly average daily temperature and total precipitation in each country and year; and \(\epsilon\) is a random disturbance term. The regression parameters include a vector of country fixed effects, \(\mu\), that control for heterogeneous unobserved time-invariant influences that vary across countries (e.g. the distribution of soil quality) (Blanc and Schlenker 2017), and a time-trend that controls for temporally-varying influences common to all countries (e.g. improved cultivars). The parameter vectors \(\beta_1\) and \(\beta_2\) define the response of log yield to average, minimum, and maximum temperature, while \(\gamma_1\) and \(\gamma_2\) define the response of log yield to average, minimum, and maximum precipitation.

We also present the differences in partial responses of crop yields to weather variable across countries and future climate scenarios. For the
Figure 1. Reported (FAO) and model predicted annual yields for (a) maize and (b) rice, top six producers. Training (1961–1985) and testing (1986–2001) data are shown as solid and dashed lines, respectively, and model specifications are indicated by color, full model (blue) and control variables only (gray).

$k$th attribute, the fitted values of the parameters (indicated with a ‘hat’) imply the following semi-elasticities of yield to temperature and precipitation,

\[ \eta_T^k = \frac{\partial \log Y}{\partial T^k} = \hat{\beta}_1^k + 2\hat{\beta}_2^k T^k \tag{2a} \]

\[ \eta_P^k = \frac{\partial \log Y}{\partial P^k} = \hat{\beta}_1^k + 2\hat{\beta}_2^k P^k \tag{2b} \]

which indicate the percentage change in yield in response to small changes in the average, minimum, and maximum temperatures and precipitation levels to which crops are exposed. Finally, following (Blanc and Schlenker 2017), the fit of our reduced-form yield model was assessed using a cross-validation test using a holdout sample of historical yields and weather. The years 1961–1985 were used to estimate the parameters of equation (1) and the fitted model was forced with the withheld data from 1986–2001. These results are compared to reported FAO yields (see section 3.1).
2.2. Impact projections

We assess the effects of future meteorology on yields under two representative concentration pathway scenarios of radiative forcing pathways, RCPs 4.5, and 8.5. Monthly average temperature and monthly total precipitation fields from the CCSM4, GFDL, and HadGEM ES models for the 2006–2099 future periods (Hempel et al. 2013, Warszawski et al. 2014) were processed and aggregated to the country level, as described in section 2.1, generating crop-specific datasets of average meteorological exposures, $\bar{T}_i$ and $\bar{P}_i$.

These data were combined with the fitted empirical model in equation (1) to project impacts of climate change on yields. In a stable climate, average weather in any future decade ($t = \tau$) will be the same as in the current period ($t = 0$). Therefore, in the future the impact of climate change is captured by the difference in the prediction of log yield $\phi$:

$$\phi_{i, \tau} = \log \bar{Y}_{i, \tau} - \log \bar{Y}_{i, 0} = \phi^T_{i, \tau} + \phi^P_{i, \tau}$$

(3)

whose components are aggregations of terms associated temperature and precipitation:

$$\phi^T_{i, \tau} = \beta_1 \left( \bar{T}_{\text{mean}} - \bar{T}_{i, \tau} \right) + \beta_2 \left( \bar{T}_{\text{mean}}^2 - \bar{T}_{i, \tau}^2 \right)$$

$$+ \left( \bar{T}_{i, \tau} \right)^2$$

$$+ \beta_3 \left( \bar{T}_{\text{min}} - \bar{T}_{i, \tau} \right) + \beta_4 \left( \bar{T}_{\text{max}} - \bar{T}_{i, \tau} \right)$$

(4)

$$\phi^P_{i, \tau} = z_1 \left( \bar{P}_{\text{mean}} - \bar{P}_{i, \tau} \right) + z_2 \left( \bar{P}_{\text{mean}}^2 - \bar{P}_{i, \tau}^2 \right)$$

$$+ \left( \bar{P}_{i, \tau} \right)^2$$

$$+ z_3 \left( \bar{P}_{\text{min}} - \bar{P}_{i, \tau} \right) + z_4 \left( \bar{P}_{\text{max}} - \bar{P}_{i, \tau} \right)$$

(5)

A natural interpretation of $\phi$ is the fractional change in the yield of a given crop grown in country $i$ in future period $t$ relative to the baseline yield that would otherwise obtain in a stable climate. The measure of climate change impact that we use in the paper expresses the fractional yield change (3) in ratio form, as

$$\Phi = \frac{Y_{i, \tau}}{Y_{i, 0}} = \exp (\phi) = \exp (\phi^T + \phi^P) = \phi^T \cdot \phi^P.$$

(6)

We use our transformed ESM fields to calculate equations (3)–6 at the country level over the decades 2020–2090. Deriving $T^k_\tau$ and $P^k_\tau$ and $\bar{T}^k$ and $\bar{P}^k$ from the outputs of each ESM minimizes the potential for model-specific biases to contaminate our impact estimates. Given our econometric specification, Jensen’s inequality (Jensen 1906) suggests that using temporally averaged temperature and precipitation series tends to bias impacts toward zero, as the squared terms fail to capture the true effect of high-frequency extremes. To address this problem, we first compute 3–6 on an annual basis before taking the decadal mean as the last step in our calculations.

To elucidate how yield impacts scale from the country level to world regions, we construct an aggregate version of equation (7) by taking the geometric mean of the individual factors, weighted by their base year fraction of total harvested area, $\omega_i = A_{i, 0} / \sum A_{i, 0}$:

$$\Phi = \prod_i (\Phi^T_i \cdot \Phi^P_i)^{\omega_i} = \prod_i (\Phi^T_i)^{\omega_i} \cdot \prod_i (\Phi^P_i)^{\omega_i} = \Phi^T \cdot \Phi^P.$$

(7)

3. Results

3.1. Empirical model fit and parameter significance

Time effects and per capita income are positive and statistically significant for both maize and rice. Maize yields have a statistically significant response to maximum and minimum temperature and all precipitation variables. The response of rice yields is statistically significant for all temperature and precipitation variables. (Results for all crops are presented in SI table S1.)

The results of our cross-validation tests are shown in (figure S1). The model shows some over-prediction of yields in the testing (1986–2001) vs. the training (1961–1985) data for observations with higher yields for both maize and rice. This is likely due to the parameter estimates on income, which are higher in the training data than the testing (or full) data set. This should not affect our projections of future shocks under different climate scenarios, as only the weather variables are used for projections.

Figures 1 and S2 illustrate the predicted interannual variability for the six countries with the largest harvested area, for the training and testing periods. The gray line shows the predicted values using only the control variables (time, GDP per capita, and country fixed effects), showing that while most of the long-term trend is captured by these variables, the year-to-year variation in yields can be attributed to annual weather conditions. The blue line plots the predicted yields using the full model. The model does not pick up the full range of interannual variability seen in the FAO reported yields, but tracks much of the FAO reported peaks and declines in both the
training and testing periods. Given the fairly aggregate level of the data, some dampening of the response is expected and consistent with results in (Schlenker and Roberts 2009).

There are a few notable outliers for which the control variables do a poor job of capturing the long-term trends in yields. Rice yields in Thailand are underpredicted in the training period and over-predicted yields in the testing period. This can be explained by the low rice yields in Thailand, relative to other top rice producers, which are due in part to the importance of low-yielding, higher quality, native rice varieties (e.g. Jasmine) in Thailand’s production (Titapiwatanaku 2012). Despite the poor performance in capturing the trend in rice yields in Thailand, the year-to-year changes in yields due to the weather variables are still observed. This point demonstrates the model can be used to predict shocks to yields due to changing weather conditions, as it separates the effect of longer-term processes that affect yields from the interannual weather.

3.2. Yield responses to temperature and precipitation
The projected annual yield shocks by country, RCP, ESM, and crop are available in .csv format at (available online at stacks.iop.org/ERL/15/114010/mmedia). We evaluate the temperature and precipitation semi-elasticities of yield in equation (2) for $\tilde{T}_k$ and $\tilde{P}_k$ corresponding to the average of the decades starting in 1990, 2050, and 2090. Figures 2 and S3 summarize the results for countries accounting for at least 1% of world production.

Maize and rice exhibit similar responses. Semi-elasticities of maximum (minimum) growing season temperatures are negative (positive) and increase in absolute magnitude with countries’ mean growing season temperature, becoming more negative (positive). The absolute magnitude of effect size is larger for $T_{Max}$ than for $T_{Min}$ by an order of magnitude for maize and a factor of two for rice. The effect of mean growing season temperature is not significant for maize and behaves similarly to $T_{Min}$ for rice. These results also show differential impacts across countries and scenarios. For instance, the semi-elasticities are larger, indicating that yields will decline more strongly due to a 1% increase in $T_{Max}$, in cooler locations, including the top two producers, USA and China. But these results are largest for the climate in the 1990–2000 period. As temperatures increase further, a 1% increase reduces yields by less. The semi-elasticities in the HadGEM-ES RCP8.5 in 2090 period are the smallest negative value, but this is on top of losses that have already occurred. Moderating this effect is the fact that, across RCP scenarios, the absolute impact of additional 1 °C maximum or minimum temperature declines with more vigorous future warming.

Trends in precipitation semi-elasticities are noisier, especially for rice. This phenomenon is attributable to larger interregional variability in rainfall and less agreement in precipitation patterns across ESMs. Both maize and rice show smaller positive increases in yield due to marginal changes in $P_{Min}$ and $P_{Max}$ for countries with the highest, compared to the lowest, baseline $P_{mean}$, while $P_{Max}$ shows the opposite response for maize. Semi-elasticities for statistically significant temperature parameters are 1–2 orders of magnitude larger than those for the precipitation variables (figure 2). This result is consistent
with (Lobell et al 2013), who show empirical evidence of the relatively larger strength of temperature response of rainfed maize yields in the USA versus precipitation.

Figure 3 summarizes the implications of our semi-elasticities for the partial effects of temperature and precipitation on yields of for maize and rice. Semi-elasticities for all crops, with and without CFE, are presented in the SI, Figure S4. For both mid- and late century timeframes there is considerable variation in partial impacts of precipitation and temperature for maize, across countries, ESMs, and warming scenarios. Increases (decreases) in mean precipitation tend to be associated with higher (lower) yields, for both maize and rice, while temperature change responses are quite variable across countries for maize and negative for rice.

3.3. Yield impact projections

The overall impact of the foregoing factors is given in figure 4, which shows our decadal projections of percentage changes in yield, $\Phi$, as multi-model means for different crops and warming scenarios at mid- and late-century. The moderation of yield changes with smaller radiative forcing is apparent: relative to RCP 8.5, shocks under RCP 4.5 are smaller in absolute magnitude and generally of the same sign. The net impact of changes in temperature and precipitation is universally negative for rice and slightly negative for non-tropical countries for maize, with slightly positive changes in some more tropical countries.

Figure 5 illustrates the annual cross-country variation and continental averages of yield shocks using the multi-model mean for RCP 8.5. Figure S5 shows the same information for additional crops and scenarios. In addition to showing the long-term trends and interannual variability, these panels demonstrate the large differences in response seen across individual countries for maize, with less variability across countries and over time for rice.

4. Discussion

Given that a contribution of this work is the large number of crops for which the impacts on yields due to changing climate have been estimated, we briefly summarize the continental trends for all the crops explored in this study, whose details can be found in table S3. All regions exhibit both positive and negative changes in yields, depending on the crop. On the whole, across crops and time periods, impacts tend to be the least negative in Asia, moderately negative in Europe and North America, and most negative in Australia, Africa, and Latin America and the Caribbean. Australia has the fewest and smallest yield increases, which come in step with some of the largest yield declines. Yields in Latin America and the Caribbean experience only modest increases for a few crops and in Africa decline almost uniformly. These findings for poor developing areas may be particularly relevant to economic development and food security concerns given their low per capita incomes, comparatively large share.
of GDP in agricultural activity, and high consumer reliance on domestically produced staple commodities (grains and roots/tubers). Regionally, rice yields decline by 10%-30%, although Asia, which both produces and consumes the majority of the world’s rice, is least severely impacted. Maize yields decline by less than 10% on average, with slight increases in North America.

We place our results for the USA and global averages in context of a selection of the prior literature in table1. Our estimates of damages are most in line with (Sue Wing et al 2015), with the exception of sorghum without CFE, for which our estimate shows large negative impacts compared with the small to moderately positive impacts in (Sue Wing et al 2015). Generally, the yield impact estimates in this work are less negative than prior work, particularly for USA maize, for which we and (Sue Wing et al 2015) show small positive impacts, while prior estimates of the climate impacts on USA maize show losses greater than 25%. Our maize, soybean, and wheat estimates lie within the ranges the GGCM results in (Rosenzweig et al 2014), consistent with recent work that finds the ranges of yield impacts between statistical models and GGCMs have large overlap (Moore et al 2017, Lobell and Asseng 2017).

Finally, we note some important caveats to our results. Our key drivers of impact are the mean and the range of precipitation and temperature over the growing season, but variables such as soil moisture (Ortiz-Bobea 2013) or daytime and night-time temperatures (Peng et al 2004) could potentially improve the predictive power of our econometric model. Likewise, while the timing of both rainfall and temperature exposures within the growing season matters tremendously for crop growth processes such as anthesis and maturation; incorporation of such information requires additional covariates (Schlenker and Roberts 2009, Sue Wing et al 2015) that our small country-year data samples are unlikely to have sufficient statistical power to detect. A related issue is unobserved year-to-year variation in the sub-national distributions of cultivation, planting and harvesting calendars, and irrigation, all of which potentially bias our econometric results by introducing an unknown degree of error into the calculation of the spatially and temporally averaged independent

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**Figure 4.** Average annual yield shocks (% change) circa 2050 (2046–2055) and 2090 (2086–2096), RCPs 8.5 and 4.5, multi-ESM mean.

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10Due to different metrics of yield changes (e.g. percent change for 1 °C increase in temperature) and varying climate scenarios and comparison periods, it is not possible to directly compare our results with the full suite of prior studies on this topic.
Table 1. Estimated U.S. and global yield impacts for five crops, this work and prior published estimates.

| Year   | Author                     | Region | Projection Period | Comparison Period | ESM                      | Scenario   | CFF     | Wheat | Soybean | Sorghum | Cotton | Maize |
|--------|----------------------------|--------|-------------------|-------------------|--------------------------|------------|---------|-------|---------|---------|--------|-------|
|        |                            |        |                   |                   |                          |            |         |       |         |         |        |       |
|        | Global                     |        |                   |                   |                          |            |         |       |         |         |        |       |
| This work | Global               |        | 2086–2095         | 2006–2015         | Multi-model              | RCP 8.5    | CFE     | 2%    | −15%    | 1%      | 0%     | 3%    |
|         |                            |        |                   |                   |                          |            | No CFE  | 1%    | −14%    | −55%    | 3%     | −1%   |
|         |                            |        |                   |                   |                          |            | CFE     | 3%    | −5%     | 2%      | 0%     | 1%    |
|         |                            |        |                   |                   |                          |            | No CFE  | 0%    | −4%     | −27%    | 1%     | −2%   |
|         |                            |        |                   |                   |                          |            | CFE     | −20% to 35% | −20% to 60% | 1%     | −2%   |
|         |                            |        |                   |                   |                          |            | No CFE  | −50% to 5% | −60% to 5% | 1%     | −2%   |
| 2014   | Rosenzweig et al (figure 4)| Global| 2079–2099         | 1980–2010         | Multi-model mean         | RCP 8.5    | CFE     | −20% to 35% | −20% to 60% | 1%     | −2%   |
|         |                            |        |                   |                   |                          |            | No CFE  | −50% to 5% | −60% to 5% | 1%     | −2%   |
| USA    |                            |        |                   |                   |                          |            |         |       |         |         |        |       |
| This work | USA                    |        | 2086–2095         | 2086–2095         | Multi-model mean         | RCP 8.5    | CFE     | −4%    | −11%    | 9%      | −6%    | 14%   |
|         |                            |        | (average annual change) | (average annual change) |                          |            | No CFE  | 6%    | 10%     | −53%    | −4%    | 10%   |
|         |                            |        |                   |                   |                          |            | CFE     | 4%    | −5%     | 10%     | −5%    | 3%    |
|         |                            |        |                   |                   |                          |            | No CFE  | 4%    | −4%     | −26%    | −3%    | 1%    |
|         |                            |        |                   |                   |                          |            | CFE     | −24%  |         |         |         | −40%   |
| 2015   | Miao, Khanna, Huang       | USA    | 2061–2080         |                  | HadGEM 2-ES              | RCP 8.5    | CFE     | −8%    | −43%    | 18%     | −4%    | −23%  |
|         |                            |        |                   |                   |                          |            | No CFE  | −8%    | −8%     | 18%     | −4%    | 10%   |
|         |                            |        |                   |                   |                          |            | No CFE  | −9%    | −15%    | 15%     | −11%   | 9%    |
|         |                            |        |                   |                   |                          |            | CFE     | −1%    | −1%     | 5%      | 3%     | 7%    |
|         |                            |        |                   |                   |                          |            | No CFE  | −2%    | −2%     | 4%      | 0%     | 6%    |
| 2012   | Urban, Roberts, et al     | USA    | 2030–2050         | 1980–2000         | Multi-model mean         | Multiple   | Multiple | −80% to 40% | −70% to 30% | −85% to 40% | −18%   |
| 2009   | Schlenker & Roberts       | USA    | 2070–2099         | 1960–1989         | Hadley II (shift in distribution) | Multiple   | (SRES)  | −80% to 40% | −70% to 30% | −85% to 40% | −18%   |
covariates (temperature and precipitation) and the dependent variable (country-level yields). Finally, there is the intractable problem of spatial and temporal variation in unobserved determinants of yields such as fertilizer, capital, and the state of technology, all of which represent adaptations to adverse weather shocks. To the extent that our regression fixed effects and time effects do not control for these omitted variables, our results on the impacts of adverse weather shocks may well be biased toward zero, resulting in pervasive underestimation of the true impacts of climate change. At a minimum, the likelihood that these unobservables are strongly trending over the historical record—especially in developing countries—makes them a prime suspect for the difficulty we face in identifying the influence of the CFE.

Notwithstanding these limitations, there are many benefits to this approach. Yield impacts can be estimated for all country-crop combinations for which sufficient historical data exist. Country-level impacts enable economic analysis at a global level, such as those conducted by IAMs. Further, consistent estimates of yield shocks can be used across multiple IAMs, which have different regional and crop aggregations. Future yield impacts can be easily estimated for any future climate change scenario. Finally, yield impacts are estimated annually, enabling economic analyses to move beyond the effects of longer-term trends to the effects of interannual variability in yields.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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References

Baker J S, Havlík P, Beach R, Leclère D, Schmid E, Valin H and Mcfarland J 2018 Evaluating the effects of climate change on US agricultural systems: sensitivity to regional impact and trade expansion scenarios Environ. Res. Lett. 13 064019

Blanc E and Schlenker W 2017 The use of panel models in the assessments of climate impacts on agriculture Rev. Environ. Econ. Policy 11 22

Elliott J, Muller C, Deryng D, Chryssanthacopoulos J, Boote K, Buchner M and Sheffield J 2015 The global gridded crop model intercomparison: data and modeling protocols for phase 1 (v1.0) Geos Model Dev. 8 17

FAO 2018 FAOSTAT Database. Food and Agriculture

Organization of the United Nations, Statistics Division

Feenstra R C, Inklaar R and Timmer M P 2015 The next generation of the pnn world table, forthcoming American economic review Amer. Econ. Rev. 105 33

Hempel S, Frieler K, Warszawski L, Schewe J and Piontek F 2013 A trend-preserving bias correction—the ISI-MIP approach Earth Syst. Dynam. 4 219–36

IPCC 2014a Climate change 2014: impacts, adaptation, and vulnerability. part A: global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, United Kingdom and New York, NY, USA:Cambridge University Press

IPCC 2014b Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (Cambridge, United Kingdom and New York, NY, USA: Intergovernmental Panel on Climate Change)

Jensen J 1906 Sur les fonctions convexes et les inégalités entre les valeurs moyennes Acta Math. 30 19

Lobell D, Cahill K and Field C 2007 Historical effects of temperature and precipitation on California crop yields Clim Change 81 187–203

Lobell D B and Asseng S 2017 Comparing estimates of climate change impacts from process-based and statistical crop models Environ. Res. Lett. 12 015001

Lobell D B and Burke M B 2010 On the use of statistical models to predict crop yield responses to climate change Agric. For. Meteorol. 150 1443–52

Lobell D B and Field C 2007 Global scale climate-crop yield relationships and the impacts of recent warming Environ. Res. Lett. 2 7

Lobell D B, Hammer G L, Mclean G, Messina C, Roberts M J and Schlenker W 2013 The critical role of extreme heat for maize production in the United States Nat. Clim. Change 3 497

Mistry M N, Sue Wing I and De Cian E 2017 Simulated vs. empirical weather responsiveness of crop yields: US evidence and implications for the agricultural impacts of climate change Environ. Res. Lett. 12 075007

Moore F C, Baldos U L C and Hertel T 2017 Economic impacts of climate change on agriculture: a comparison of process-based and statistical yield models Environ. Res. Lett. 12 065008

Müller C, Elliott J, Chryssanthacopoulos J, Arneth A, Balkovic J, Ciais P and Yang H 2017 Global gridded crop model evaluation: benchmarking, skills, deficiencies and implications Geos. Model Dev. 10 20

Nelson G C, Valin H, Sands R D, Havlík P, Ahammad H, Deryng D and Elliott J 2014a Climate change effects on agriculture: economic responses to biophysical shocks Proc. Natl. Acad. Sci. 111 3274–9

Nelson G C, van der Mensbrugge D, Ahammad H, Blanc E, Calvin K C, Hasegawa T and Havlik P 2014b Agriculture and climate change in global scenarios: why don’t the models agree Agr. Econ. 45 17

Ortiz-Bobea A 2013 Understanding temperature and moisture interactions in the economics of climate change impacts and adaptation on agriculture. Paper presented at the Agriculture and Applied Economics Association’s 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4–6 2013

Peng S, Huang J, Sheehy J E, Laza R C, Vesperas R M, Zhong X and Cassman K G 2004 Rice yields decline with higher night temperature from global warming Proc. Natl. Acad. Sci. USA 101 9971–5

Portmann F T, Siebert S and Döll P 2010 MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling Global Biogeochem. Cycles 24 1

Rosenzweig C, Elliott J, Deryng D, Ruane A C, Müller C, Arneth A and Boote K J 2014 Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison Proc. Natl. Acad. Sci. 111 6

Sacks W J, Deryng D, Foley J A and Ramankutty N 2010 Crop planting dates: an analysis of global patterns Global Ecol. Biogeogr. 19 14

Schlenker W, Rolinski S and Müller C 2016 A network-based approach for semi-quantitative knowledge mining and its application to yield variability Environ. Res. Lett. 11 123001

Schlenker W and Roberts M J 2009 Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change Proc. Natl. Acad. Sci. 106 15594–8

Schmitz C, van Meijl H, Kyle P, Nelson G C, Fujimori S, Gurgel A and Havlík P 2013 Land-use change trajectories up to 2050: insights from a global agro-economic model comparison Agr. Econ. 45 69–84

Sue Wing I, Monier E, Stern A and Mundra A 2015 US major crops’ uncertain climate change risks and greenhouse gas mitigation benefits Environ. Res. Lett. 10 115002

Thomas T 2015 US maize data reveals adaptation to heat and water stress IFPRI Discussion Paper 1485

Titapiwatanakul B 2012 The rice situation in Thailand Technical Assistance Consultant’s Report TA-REG 7495 Asian Development Bank

Waldhoff S T, Wing I S, Beach R, Cai Y, Daenzer K, Ren X and Climate change in the 21st century in a global gridded crop model intercomparison Proc. Natl. Acad. Sci. 111 6

Waldhoff S T, Wing I S, Beach R, Cai Y, Daenzer K, Ren X and Climate change in the 21st century in a global gridded crop model intercomparison Proc. Natl. Acad. Sci. 111 6

Weatherstone M C, Viterbo P, Shuttleworth W J, Blyth E, Oosterhuis H and Adam J C 2011 Creation of the WATCH forcing data and its use to assess global and regional reference crop evaporation over land during the twentieth century J. Hydrometeorol. 12 823–48