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LETTER

# Empirical estimation of weather-driven yield shocks using biophysical characteristics for U.S. rainfed and irrigated maize, soybeans, and winter wheat

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Supplementary material for this article is available online

## Abstract

Agricultural yields are highly susceptible to changes in weather system patterns, including annual and sub-annual changes in temperature and precipitation. The impacts of future meteorological variable changes on crop yields have been widely studied in both empirical and process-based models. These changes in future yields can be used in economic models to adjust future crop yields or production functions to reflect the effects of changing weather conditions. This work presents an econometric approach that combines historical weather data with the biophysical growth cycles of maize, winter wheat, and soybean to predict the year-to-year weather-driven yield shocks for rainfed crops. Temperature and modeled soil moisture are taken as predictors, allowing testing of the fitted rainfed model's ability to predict shocks to irrigated yields by assuming irrigation produces the yield-maximizing level of soil moisture. This approach enables prediction of the potential impacts of changing weather patterns on irrigated crops in areas that are currently primarily rainfed. We present the results of the empirical model, fitted with rainfed data; out-of-sample validation on irrigated crops; and projections of yield shocks under multiple future climate scenarios. Under a bias-corrected GFDL RCP8.5 scenario, this approach predicts the average of annual weather-induced yield shocks, relative to the average of 2006–2020 annual yield shocks, across U.S. counties in the 2040–2060 period of −17% and −13% for rainfed and irrigated maize, −19% and −18% for rainfed and irrigated soybean, and −4% and −2% for rainfed and irrigated winter wheat. Predicted changes in the 2070–2090 period are −30% and −29% for rainfed and irrigated maize, −33% for both rainfed and irrigated soybean, and −7% and −5%for rainfed and irrigated winter wheat. The annual yield shocks presented here will enable modeling of the economic consequences of extreme weather events and potential for irrigation to mitigate such events.

## 1. Introduction

Understanding the implications of changing weather patterns on economic outcomes such as crop prices, trade, water demand for irrigation, and food security requires projections of weather-driven crop yield shocks under multiple future climate scenarios that can be incorporated into economic models that include assumptions about changes in agricultural productivity due to technology change. In particular, the annual yield produced in any given location will be driven by sub-annual weather patterns in that location to deviate from a non-weather trend, and irrigated crops may be differently impacted than rainfed. Crop yields, in turn, can be input to economic models to explore impacts on both water and economic considerations [1, 2]. For example, in some regions, irrigation may become a primary management practice to offset the impacts of these changing weather patterns, including regions that are currently exclusively rainfed. Therefore, a method for estimating annual, weather-driven yield shocks must be able to be extended to project shocks to irrigated crops even in such regions.

Econometric approaches to estimating climate impacts on crop yields have been widely studied in the empirical economic literature, however these studies have been largely limited to rainfed agriculture or not differentiated between rainfed and irrigated crops, limiting their usefulness for studies that explore the role of irrigation as an adaptive strategy [3–12]. Further, these studies generally use a reduced form, rather than structural, modeling approach with aggregate variables, such as growing degree days, maximum, minimum, or mean values over the course of a year or growing season as the primary weather variable. Some empirical modeling works take similar approaches to this work, focusing on biophysical growth stages, meteorological and subseasonal predictors [13–16] or differentiating between irrigated and rainfed yield prediction [17–20]. However, these works do not explicitly isolate weather-driven impacts on crop yields from economic-driven trends, creating a potential double counting of the technology-driven yield productivity changes when using their predicted yields in economic models, which feature their own assumptions about technology and economically-driven yield productivity changes. Many of the works differentiating between irrigated and rainfed responses also focus on specifc sub-regions that are currently irrigated. Finally, process-based, global gridded crop models [21, 22] can be difficult to calibrate to field conditions in a sufficiently broad range of climates and are computationally expensive to run [16], making their dynamic incorporation with economic models to understand the impacts of changing crop yields on economic, water, and other factors challenging.

To address these challenges, we estimate an empirical model of the annual yield shocks due to monthly temperature and soil moisture for rainfed maize, soy, and winter wheat, utilizing key crop-specific growth stages, using historical U.S. county-level data. We then conduct an out-of-sample validation exercise, using the rainfed model to predict yields in currently irrigated areas, assuming irrigation achieves the numerically optimal soil moisture. One key novelty of this work is the use of an econometric model utilizing meteorological values and soil moisture at biophysically important growth stages, allowing for the use of data even with spatial differences in growing season. This differs from prior work that has taken used annual summary weather values as predictors and results in weather-driven yield shocks that can be ingested by economic models for a variety of crops and management practices. Example projections of these weather-driven yield shocks under RCP4.5 and RCP8.5 are provided in section 4. Additionally, the methods used for projection of weather shocks on irrigated crops in areas without wide-spread irrigation enable future analysis of the role of irrigation as an adaptive management practice to changing growing conditions. The irrigated and rainfed annual weather-driven yield shocks presented here will further enable future modeling of the economic consequences of extreme weather events by serving as inputs to economic models. These economic models generally include their own socioeconomically driven agricultural productivity time series that differ for irrigated and rainfed management practices. By applying irrigated and rainfed weather-driven yield shocks to the socioeconomically driven productivity time series, the economic models can achieve differentiated, weather-impacted projections of irrigated and rainfed yields.

## 2. Methods

### 2.1. Data

We create a panel dataset for U.S. counties from 1977 to 2001 of monthly average temperatures and modeled soil moisture for months corresponding to key growth stages for rainfed and irrigated maize, soybean, and winter wheat. We use the data sources specified in table 1 to create a fixed effects panel model that relates the logarithm of reported yields to various predictors and takes into consideration collinearities among time, state real GDP *per capita*, atmospheric $CO_2$, soil moisture, and temperature (equation (1) and table 1). This model for logarithm of yields is then used to create the weather-driven yield shock estimates of interest (section 2.2 for details). Table 2 identifies the growth stages of interest for each crop.

Uncertainty in the growing season data used, county-to-county inconsistencies in years of yield and harvested area data reported to the United States Department of Agriculture (USDA) for each county and each crop, and uncertainty in the estimation of soil moisture are all challenges for empirical estimation of crop yields. For example, key growth stages identified for maize are the period from planting to emergence, silking, and denting (see table 2 for stage details). The precise timing of these stages must be collected by on-the-ground crop observers and vary from field to field, limiting data coverage and specificity [23]. Data on the timing of these stages is collected on a weekly basis in the United States and varies even within a county or state [23, 24]. This inherent uncertainty in the timing of crop maturation means that any daily estimate of growth stages would be unrealistic. Therefore, this model uses statewide crop stages for each crop, taken as the median month of all available historical stages across years for that state and crop. The monthly average measures of temperature and precipitation (via soil moisture) for the month, specified by each stage, are used in the estimation. This approach allows for more sub-annual meteorological

**Table 1.** Data sources used for modeling in this work.

| Quantity | Citation | Notes |
|---|---|---|
| Temperature and precipitation values, historic atmospheric $CO_2$ | WATCH data [28] | WATCH bias-corrected data is only available through 2001. |
| County-level yield and harvested area for irrigated and rainfed crops. | USDA NASS [29] | Counties with fewer than eight years of data were discarded. |
| State-level real GDP *per capita* | BEA [30–34] | Units of constant 2012 U.S. dollars. The availability of BEA real GDP *per capita* data dictates the modeling start year of 1977. |
| Soil available water capacity map | USDA SSURGO soil map [35] | |
| Modeled soil moisture | Xanthos hydrology model [25] | Inputs are the USDA SSURGO map, bias-corrected gridded temperature and precipitation data from WATCH. An area-weighted average of soil water holding capacity was used for each county. Potential evapotranspiration is then calculated using the Thornthwaite method [36] and runoff, percolation, and retained soil moisture are calculated using methods from the global water availability model [37]. |
| Growing season calendars by state and crop | USDA National Agricultural Statistics Service [23] | Identify the month in which each growth stage for each crop in each state occurs with the median month across available years and reported counties. For states with only a subset of stages reported, missing stages are filled in based on the length between stages in other states. |

**Table 2.** Selected growth stages selected for each crop. The names of growth stages used in this table were chosen for consistency with variable names in the reported model parameter estimates given in the supplementary material (available online at stacks.iop.org/ERL/16/094007/mmedia). When the USDA provides stage data for stages only a few days apart, the inclusion of both stages would result in perfectly collinear weather data for two stages, so only one stage is used.

| Crop | Stages |
|---|---|
| Maize | • *Emergence*: average temperature and soil moisture across months from planting to emergence of the first leaves above the soil surface.<br>• *Silking:* temperature and soil moisture for month in which the emergence of silks from the husk occurs.<br>• *Denting*: temperature and soil moisture for month in which denting of most maize kernels occurs. |
| Soybeans | • *Emergence*: average temperature and soil moisture across months from planting to emergence of the first leaves above the soil surface.<br>• *Setting*: temperature and soil moisture for month in which the development of small pods occurs.<br>• *Fully*: temperature and soil moisture for month in which crops have fully developed pods. |
| Winter wheat | • *Proxy vernalization*: minimum temperature across months between planting and emergence of the first leaves about the soil surface as a proxy for vernalization.<br>• *Jointing*: temperature and soil moisture in the month prior to heading (roughly corresponding to the jointing stage, when the growing point is above the soil surface).<br>• *Heading*: temperature and soil moisture in the month of the heading stage, when the wheat head is completely emerged. |

detail than found in past studies using annual maximum, mininimum, and/or average variables. Additionally, this approach provides a more direct biophysical connection between weather data and yield with fewer parameters to estimate than directly using the meteorological data in each month of the growing season (e.g. first month temperature, second month temperature, etc). It also enables the training of a single model across counties with differing growing season lengths and timings. The soil moisture model used for this work, Xanthos (see table 1 for details), has been extensively benchmarked to runoff and streamflow in both observation and other hydrology models and relies on bias-corrected data [25, 26]. This cannot eliminate uncertainty, especially in future projections. However, the consistent use of the same model's soil moisture as a predictor in the historical period, where validation of modeled quantities is possible, and the future helps ensure that we do not introduce new sources of error via inconsistencies between the historic and future periods when presenting our example projections.

For demonstration, two Earth system models with generally differing behavior, GFDL and HadGEM, were selected, driven by RCP 4.5 and RCP8.5, from the inter-sectoral impactmodel intercomparison project (ISIMIP-2b) bias corrected time series for these scenarios [27]. For each county, the same monthly periods for each growth stage are used in the projections as in the historical period. While farmers may change their planting and harvesting behaviors under different futures, this represents an avenue of adaptation outside of the scope of this study.

### 2.2. Empirical model

To capture the weather-driven shocks of rainfed yield ($\tilde{y}_{i,t}$) in each county $i$ and year $t$ empirically from historical data, we must first build an intermediate model relating rainfed yield ($y_{it}$) to drivers of interest. While $\tilde{y}_{i,t}$ by definition is the response of yields to weather factors such as temperature, $y_{it}$ during the historical period must also be related to state GDP *per captia*, $CO_2$, and time as all are colinear with each other and with temperature in the historical period. Therefore, they must be included as variables so that economic factors such as GDP *per capita* are not double counted when using yield shocks in economic and economic models [10].

In equation (1), we specify a model that relates the logarithm of yield (logyield, $\log(y_{it})$) to drivers of interest. It is quadratic in the temperature and soil moisture values for each key crop-specific growth stage (table 2) to avoid unrealistic monotonicity in the response. Adapting the approach of Waldhoff *et al* [10], this model includes the following variables: time $t$ to represent general technological change, state real GDP *per capita* in each year $t$ for the state in which county $i$ resides ($m_{it}$) as a spatially heterogeneous proxy for access to technological changes, county-specific fixed effects for each county $i$ ($\mu_i$), and the response to global $CO_2$ concentrations, (parameterized by $\theta$). The response to global $CO_2$ concentrations varies only over time and not space [38]. Temperature ($T_{it}^k$) and soil moisture ($SM_{it}^k$) for each county is taken at crop specific growth stages $k$ (given in table 2) in each year. County specific random error from the linear regression is captured in the term $u_{it}$.

Parameters are estimated from the rainfed yield data using harvested area-weighted least squares for each crop. This more heavily weights counties that are major agricultural producers. This is chosen for two reasons. First, the responses to weather in regions with more harvested area will be less confounded by very localized conditions, such as nutrient deficiencies or poor drainage. Second, the goal of this work is a flexible and reliable method for estimating annual weather-driven yield shocks for use in national or global economic models and the economic outcomes will be more dependent on larger producing regions. The estimated parameters are provided in the supplementary material, tables SM1 (maize), SM3 (soybeans), SM5 (winter wheat)

$$\begin{aligned}\log(y_{it}) = {} & \mu_i + \lambda \log t + \chi \log m_{it} + \theta \log([CO_2]_t \\ & - [CO_2]_{\min} + 1) \\ & + \sum_k \left[\alpha_1^k T_{it}^k + \alpha_2^k \left(T_{it}^k\right)^2\right] \\ & + \sum_k \left[\beta_1^k SM_{it}^k + \beta_2^k (SM_{it}^k)^2\right] + u_{it} \\ := {} & s\phi\,(\text{county fixed effect}_i) \\ & + \phi\,(\text{non - weather variables}_{it}) + \phi\,(T_{it}) \\ & + \phi\,(SM_{it}) + u_{it}. \qquad (1)\end{aligned}$$

In equation (1), logyield was used for estimating parameters in the rainfed models so that the yield in county $i$, in year $t$, can be decomposed multiplicatively to separate the weather impacts from the non-weather variables, shown in equation (2)

$$y_{it} = \exp\left(\begin{array}{c}\mu_i + \lambda \log t + \chi \log m_{it} + \\ \theta \log([CO_2]_t - [CO_2]_{\min} + 1) + \\ \sum_k [\alpha_1^k T_{it}^k + \alpha_2^k \left(T_{it}^k\right)^2\Big] + \sum_k [\beta_1^k SM_{it}^k + \beta_2^k \left(SM_{it}^k\right)^2\Big]\end{array}\right) \exp(u_{it}) \qquad (2)$$
$$:= \Phi\,(\text{county fixed effect}_i)\,\Phi\,(\text{non} - \text{weather variables}_{it})\,\Phi\,(T_{it})\,\Phi\,(SM_{it})\exp(u_{it})\,.$$

These models are intended to provide multipliers capturing weather impacts, rather than to estimate actual yields. In a stable climate, average weather in any future period (with individual years denoted by $t = \tau$) will be the same as in the current period (individual years in this period denoted by $t = t_0$). Therefore, the impact of climate change is captured by the change in the prediction of weather-sensitive yield ($\log \tilde{y}_{i,t} = \phi_{i,t}^T + \phi_{i,t}^{SM}$), between 0 and $\tau$

$$impact(\tau) = \frac{mean_{\{t\in\tau\}}\tilde{y}_{i,t}}{mean_{\{t\in t_0\}}\tilde{y}_{i,t}} = \frac{mean_{\{t\in\tau\}}\left[\Phi(T_{it})\,\Phi(SM_{it})\right]}{mean_{\{t\in t_0\}}\left[\Phi(T_{it})\,\Phi(SM_{it})\right]} \quad (3)$$

This results in a weather impact multiplier that may be used by economic models, which have exogenous assumptions for improvements in yields for different agricultural technologies, preventing double counting of these factors.

### 2.2.1. Irrigated responses

For each crop, we also test the fitted model on irrigated data, with the assumption of perfect minimum irrigation. Rather than estimating parameters for equation (1) using data for irrigated areas specifically, this method increases the spatial range across which the weather-driven yield shocks on irrigated crops may be applicable, as far fewer counties have historically used irrigation than have relied on rainfall. This increased spatial range improves the ingestibility of these shocks by economic models. Note that this makes the validation of irrigated responses on irrigated historical data a fully out of sample test for this modeling approach, as no irrigated data is used in estimating the parameters in equation (1) (and by extension, equation (4)).

Perfect irrigation is numerically estimated from equation (1) for each growth stage $k$, $\mathrm{SM}^k_{\mathrm{optimal}} = \frac{-\beta^k_1}{2\beta^k_2}$ (the quantity that maximizes logyield with respect to each growth stage's soil moisture). Then equation (1) is used to predict irrigated logyields with soil moisture values in each stage as follows:

$$\mathrm{SM}^{k,\,\mathrm{irrigated}}_{it} = \max\left(\mathrm{SM}^k_{\mathrm{optimal}},\ \mathrm{SM}^k_{it}\right) \quad (4)$$

where $\mathrm{SM}^k_{it}$ are the county soil moisture values as in equation (1). $\mathrm{SM}^k_{\mathrm{optimal}}$ values are recorded for each crop in the supplementary material (tables SM1–6). By using the soil moisture value for irrigated crops described in equation (4), heavy precipitation months have negative impacts on irrigated yields, to the extent that this behavior exists in the respective rainfed model, while also assuming that the worst negative effects of low soil moisture are avoided. Negative shocks due to high temperature levels are still captured. The amount of water necessary to achieve $SM^k_{optimal}$ in the real world will vary with weather conditions. In many of the economic models that ingest the weather shocks described in this work (e.g. the Global Change Analyisis Model [39]), only perfectly irrigated and entirely rainfed management practices are modeled. In these models, changes to water availability under varying weather conditions will impact the prices of water for irrigation and therefore the total land allocated to perfect irrigation will vary as well.

## 2.3. Model evaluation

As discussed, this work is not intended to produce future projections of actual yields, only weather-driven yield shocks. However, the observational data available for model evaluation includes both weather impacts and non-weather factors, making direct evaluation of weather only impacts (equation (3)) impossible for either rainfed or irrigated data. Therefore, we do evaluate the simulated logyields given by equation (1) against historically observed log yields.

### 2.3.1. Training data and out of sample tests

To test the ability of the model to project yield impacts beyond 2001, we undertake multiple tests for each crop.

We conduct two out-of-sample validation exercises. We first test the ability of the rainfed fitted model to project rainfed centered logyields out-of-sample temporally. We train the model using rainfed data in each county from 1977 to 1996, and use this parameterization to predict centered logyields in the 1997–2001 period. Our strongest out-of-sample test is to use the model fitted on the full sample of rainfed observations to predict centered logyields for irrigated areas, with the assumption of numerically optimal soil moisture. Good model performance on irrigated data is a key test of this work and supports the use of this model to project future yield shocks in irrigated areas, including areas that are not currently irrigated. The parameters estimated from this subset of data are given in in the supplementary material, tables SM2 (maize), SM4 (soybeans), SM6 (winter wheat).

### 2.3.2. Model evaluation

Simulated logyield data in each county (equation (1)) are evaluated against observational data primarily using a normalized centered root mean square (cNRMS) error metric [40–42]. That is, the error in county $i$ is given by:

$$\mathrm{error}^2_i = \frac{\mathrm{mean}\left(\left(\left(\mathrm{sim}_{it} - \overline{\mathrm{sim}_{it}}\right) - \left(\mathrm{obs}_{it} - \overline{\mathrm{obs}_{it}}\right)\right)^2\right)}{\mathrm{var}\left(\mathrm{trainingObs}_i\right)}. \quad (5)$$

A normalized metric allows for a judgement of acceptable versus unacceptable model performance in each county [40, 41]. The closer $\mathrm{error}_i$ is to 0, the better the performance of the model in that county. Counties where $\mathrm{error}_i \geqslant 1$ are deemed to have unacceptably poor model performance, as the deviations between simulated and observed quantities in that county are larger than the historical variance in the data used to estimate parameters. Throughout this work, we refer to *centered data* when we have removed the means, as in our error metric. A centered error metric is chosen to evaluate model performance because it disregards vertical offset errors between simulated and observed logyields, which fully cancel out when calculating weather-driven yield shocks (equation (3)) and are therefore irrelevant. Additional details relating to this metric are included in supplementary material section 2.

For the out of sample tests on irrigated data, we adjust this metric to be:

$$\text{error}_i^2 = \frac{\text{mean}\left(\left(\left(\text{sim}_{it} - \overline{\text{sim}_{it}}\right) - \left(\text{obs}_{it} - \overline{\text{obs}_{it}}\right)\right)^2\right)}{\text{var}\left(\text{historicalObs}_i\right)}. \tag{6}$$

The error given by equation (6) compares the root mean square error in the predicted irrigated logyields to the variance of the historical irrigated data to see if using the mean of the irrigated data would have resulted in a better prediction than our fitted model, rather than the mean of the rainfed data as in equation (5).

## 3. Model evaluation results and discussion

We present maize results in detail initially, followed by analysis of soybean and winter wheat results. Model performance for both rainfed and irrigated crops are included.

### 3.1. Maize

Overall, we judge that the model described in equation (1) performs well for both rainfed and irrigated maize. Performance is measured by the percent of counties with $\text{error}_i < 1$ (acceptable model performance) for the cNRMS error metric given in equation (5), and by the average value across counties of cNRMS < 1.

From table 3, the temporal out of sample test (rows 1 and 2) results in good performance; a large percentage of counties have acceptable model performance, and the average error across counties is less than one. The predictions with parameters estimated from all 1977–2001 rainfed data result in good model performance on both rainfed (row 3) and irrigated (row 4) yields as well. Performance is better on the rainfed data (the training data) than on the irrigated data (out of sample). We find good model performance, with more than 77% of out of sample counties having acceptably predicted centered logyields.

The numerical evaluation of model performance in table 3 suggests that this model performs well on maize across a suite of tests. To verify, we look at the cNRMS at the county-level. Figure 1 plots the cNRMS value in each county versus the average harvested area in the county for rainfed (left) and irrigated (right) crops. In both cases, we see that the counties with unacceptable performance tend to be those with smaller harvested area. The poorer performance in smaller-producing counties is not surprising, given that we explicitly weight those counties less in the estimation of model parameters and the effects of highly localized conditions are likely to be more pronounced. Further, the eventual economic impacts of weather shocks on crop production modeled here will be more dependent on the larger producing areas.

While error metrics are useful for checking overall model performance across many counties, we include time series for a selection of counties to highlight model performance at capturing year to year variability of the centered logyields within individual counties. Figure 2 plots the predicted and observed centered logyields for the nine largest producing rainfed counties over time (average production 35.61 million bu). The same quantities are examined for the nine largest of the poor performing rainfed counties (average production 6.89 million bu) in figure 3. All of the poor performing counties feature either small average production or several consecutive years of missing data (or both). Finally, figure 4 plots the predicted and observed centered logyields for the nine largest producing irrigated counties over time. Taken together with table 3 and figure 1, this model is judged to have good performance for both rainfed and irrigated maize. Across all three sets of time series figures, it is clear that the model does struggle to predict extreme events in some counties (e.g. 1986, 1991, 1993). Given that these extremes often result in reduced harvested area relative to non-extreme years, and are therefore weighted less when estimating our parameters, this is not surprising. Further, flooding events (1993) are challenging to capture with a soil moisture model that saturates at 100% with no additional measures of degrees of flooding. There will also be some highly spatially specific events that an approach such as ours, seeking to generalize over wide spatial regions for use in even more spatially aggregated economic models, cannot capture. For example, the subset of counties in figure 2 that struggle to capture 1991 events are in close proximity to each other in Illinois, suggesting a local weather factor beyond temperature and soil moisture was relevant at this time. The quantitative evaluation represented by table 3 and figure 1 do suggest, however, that most events in most counties are well captured.

### 3.2. Other crop

The same modeling approach is applied to soybeans (table 4, figure SM8) and winter wheat (table 5, figure SM9) using appropriate growth stages. Overall, we find good model performance for both soybean and winter wheat. A large percentage of counties (70% or more) have acceptable model performance and the average error across counties is less than one in all evaluations for both crops. As with maize, the counties with the worst performance are generally those with small harvested areas for both soybean and winter wheat. Time series similar to figures 2–4 are provided for soybeans and winter wheat in the supplementary material (figures SM2–4 for soybean, SM5–7 for winter wheat).

**Table 3.** Performance of maize model on rainfed and irrigated data. The data evaluated with cNRMS (equation (5)) in each row is specified. The weighted average of cNRMS weights each county's cNRMS value by its mean harvested area over the sample period. The different grayscale shadings correspond to our two out of sample tests, indicating pairs of results that should be compared to each other. The light grey pair is a temporal out of sample validation for the rainfed data. The dark grey pair is a validation of the model defined in equations (1)–(4), trained on rainfed data, and evaluated on the entirely out of sample irrigated data.

| Model training data | Years of data evaluated with cNRMS | Crop management evaluated with cNRMS | Number of counties | Percent acceptable counties | Avg cNRMS across counties | Weighted Avg cNRMS across counties |
|---|---|---|---|---|---|---|
| All rainfed data 1977–1996 | 1977–1996 | Rainfed (training data) | 2291 | 89.0% | 0.807 | 0.742 |
| All rainfed data 1977–1996 | 1997–2001 | Rainfed (temporal out of sample) | 2291 | 88.6% | 0.627 | 0.499 |
| All rainfed data 1977–2001 | 1997–2001 | Rainfed (training data) | 2291 | 89.4% | 0.794 | 0.709 |
| All rainfed data 1977–2001 | 1977–2001 | Irrigated (completely out of sample) | 401 | 77.3% | 0.905 | 0.822 |

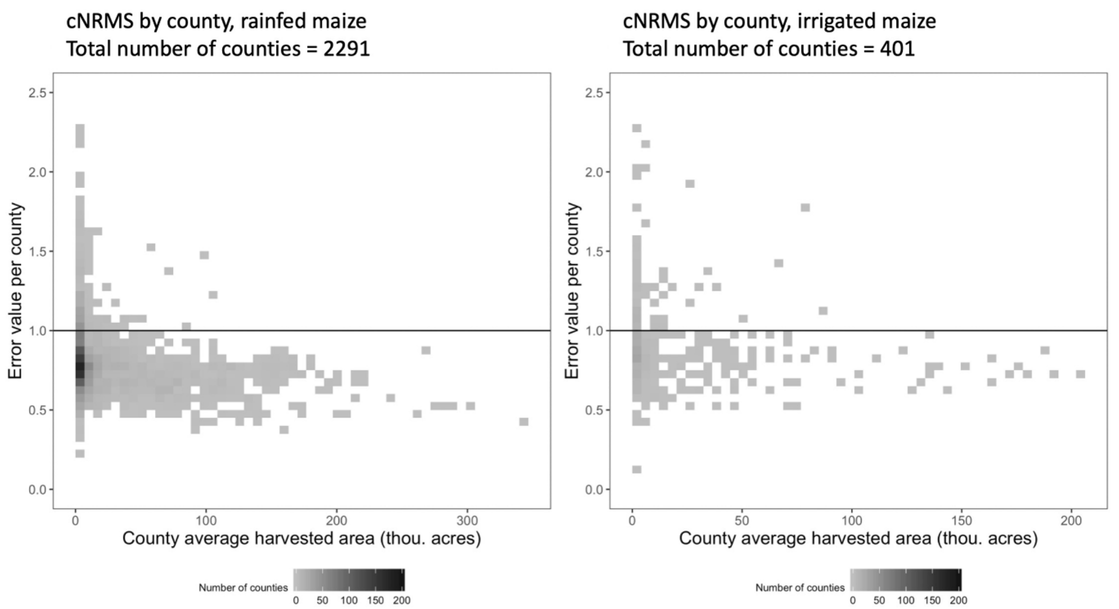


**Figure 1.** Heatmap of average harvested area versus cNRMS of simulated yields from the parameters trained from all rainfed maize data from 1977 to 2001. A reference line for acceptable performance at cNRMS = 1 is included. Left: rainfed data. Right: irrigated data.

## 4. Weather-driven yield shock results and discussion

To examine the spatial distribution of impacts into the 21st century, we use the ISIMIP-2b bias corrected time series for GFDL and HadGEM driven by RCP 4.5 and RCP8.5 [27] to create the weather-driven yield shocks (equation (3)) for rainfed and irrigated maize, soybeans, and winter wheat.

To examine whether the general patterns of future yield shocks are consistent with expectations given the general patterns of projected changing temperature and soil moisture, we present visual summaries of these quantities in figures 5–7. Taking maize as an illustrative example, figure 5 (top row) shows the GFDL RCP4.5 average annual temperature and soil moisture levels in the 2070–2090 period for the key growth stages of table 2[3]. Figure 5 (bottom row) plots the average yield shocks due to weather during this period, as a fractional change from a 2006–2020 average baseline. Table 6 shows that irrigation helps to avoid the most extreme negative shocks, but it is not a panacea. While some specific modeling studies in smaller spatial regions find that irrigation can entirely offset heat stress, our finding that irrigation is beneficial but not a panacea across a broad spatial range is consistent with results from other modeling works (e.g. [17, 22]).

Figures 6 and 7 is the same for the two Earth System Models (ESMs), GFDL and HadGEM RCP8.5

[3] Note that these are not actual inputs used to calculate weather-driven yield shocks in equation (3), but rather an illustration of the general trend in weather changes.

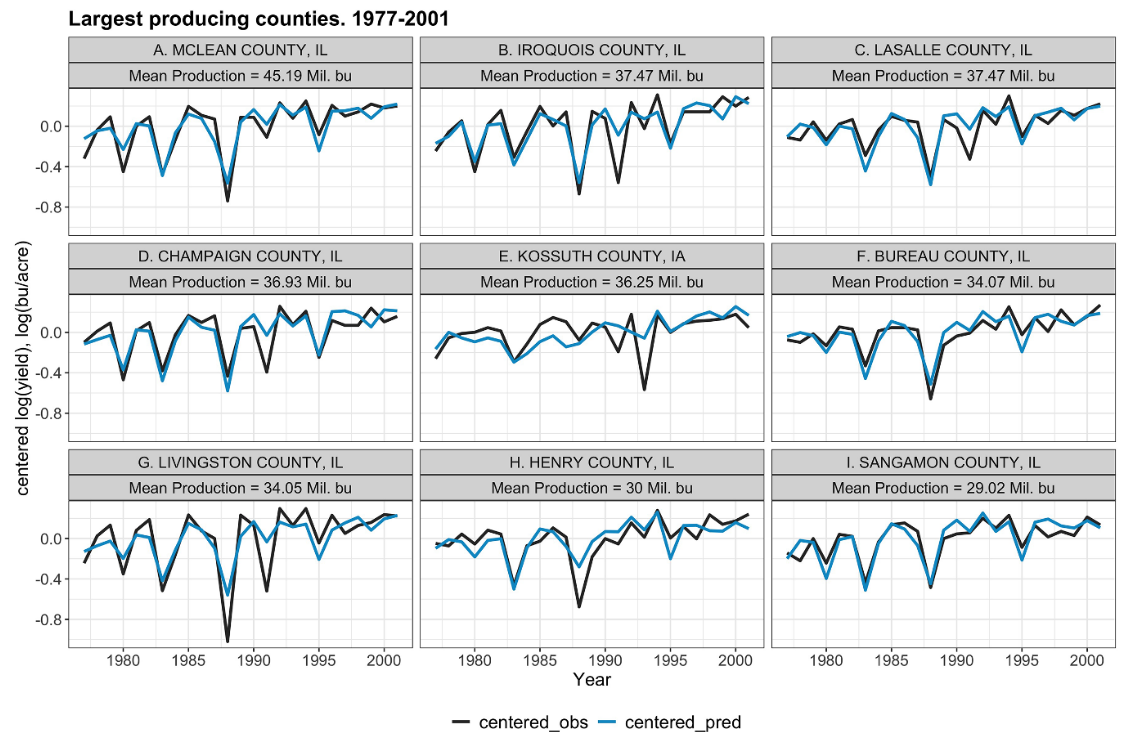


**Figure 2.** Times series of observed and predicted centered logyields for the nine largest rainfed maize producing counties, from the parameters estimated from all rainfed maize data from 1977 to 2001.

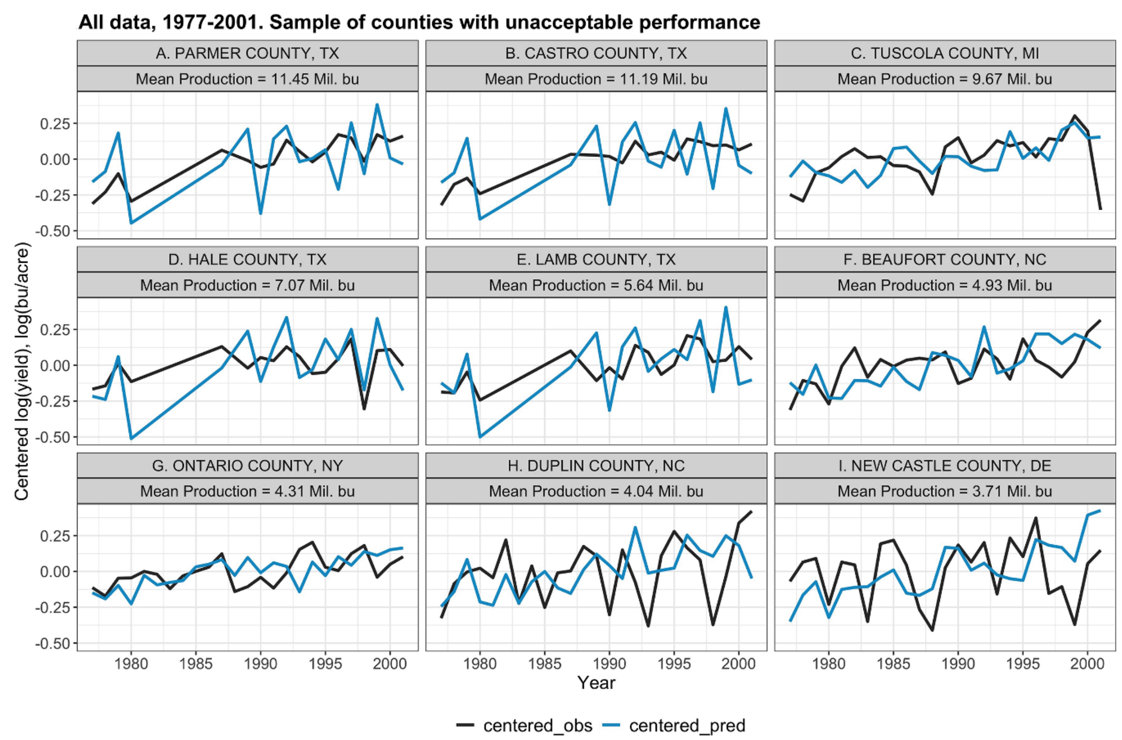


**Figure 3.** Times series of observed and predicted centered logyields for the nine largest rainfed maize producing counties with unacceptable model performance, from the parameters estimated from all rainfed maize data from 1977 to 2001.

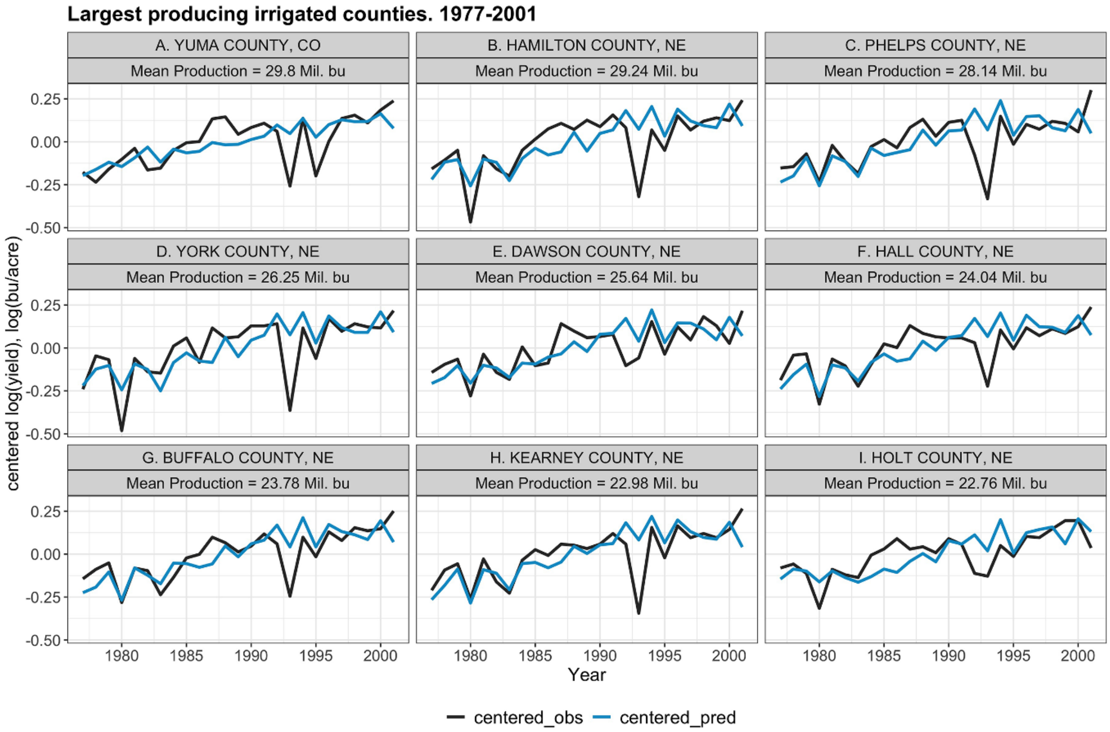


**Figure 4.** Times series of observed and predicted centered logyields for the nine largest irrigated maize producing counties, from the parameters estimated from all rainfed maize data from 1977 to 2001.

**Table 4.** Performance of soybean model on rainfed and irrigated data. The data evaluated with cNRMS (equation (5)) in each row is specified. The weighted average of cNRMS weights each county's cNRMS value by its mean harvested area over the sample period. The different grayscale shadings correspond to our two out of sample tests, indicating pairs of results that should be compared to each other. The light grey pair is a temporal out of sample validation for the rainfed data. The dark grey pair is a validation of the model defined in equations (1)–(4), trained on rainfed data, and evaluated on the entirely out of sample irrigated data.

| Model training data | Years of data evaluated with cNRMS | Crop management evaluated with cNRMS | Number of counties | Percent acceptable counties | Avg cNRMS across counties | Weighted Avg cNRMS across counties |
|---|---|---|---|---|---|---|
| All rainfed data 1977–1996 | 1977–1996 | Rainfed (training data) | 1890 | 90.7% | 0.798 | 0.766 |
| All rainfed data 1977–1996 | 1997–2001 | Rainfed (temporal out of sample) | 1890 | 79.5% | 0.760 | 0.675 |
| All rainfed data 1977–2001 | 1997–2001 | Rainfed (training data) | 1890 | 91.4% | 0.819 | 0.776 |
| All rainfed data 1977–2001 | 1977–2001 | Irrigated (completely out of sample) | 235 | 73.2% | 0.909 | 0.953 |

respectively. The net effect in all cases is a negative trend in weather-driven yield shocks, though regions with positive impacts from weather exist, particularly in the west. Comparing RCP4.5 to the RCP8.5, where much of the spatial pattern of temperature and soil moisture are similar, but often hotter and dryer, one sees that weather impacts become more negative. Additional maps for other crops and other time slices under all four ESM-RCP combinations are provided in the supplementary data repository (location noted in supplementary material).

Table 6 provides the range of changes seen across plotted counties for both GFDL and HadGEM RCP 4.5 and 8.5 scenarios, in the periods 2040–2060 and 2070–2090. Tables 7 and 8 summarize the information for soybean and winter wheat respectively. The annual yield shock projections for each year are provided as .csv files in the zenodo archive of data for this paper (zenodo archive will be published upon acceptance, see supplementary material for details). The ranges of values reported in tables 6–8 and figures 5–7 are generally within the range of values for yield changes under these values in the literature. Additionally, the spatial patterns of impacts seen in figures 5–7 are consistent with those seen in the RCP-driven gridded results in [22].

**Table 5.** Performance of winter wheat model on rainfed and irrigated data. The data evaluated with cNRMS (equation (5)) in each row is specified. The weighted average of cNRMS weights each county's cNRMS value by its mean harvested area over the sample period. The different grayscale shadings correspond to our two out of sample tests, indicating pairs of results that should be compared to each other. The light grey pair is a temporal out of sample validation for the rainfed data. The dark grey pair is a validation of the model defined in equations (1)–(4), trained on rainfed data, and evaluated on the entirely out of sample irrigated data.

| Model training data | Years of data evaluated with cNRMS | Crop management evaluated with cNRMS | Number of counties | Percent acceptable counties | Avg cNRMS across counties | Weighted Avg cNRMS across counties |
|---|---|---|---|---|---|---|
| All rainfed data 1977–1996 | 1977–1996 | Rainfed (training data) | 1941 | 77.0% | 0.948 | 0.924 |
| All rainfed data 1977–1996 | 1997–2001 | Rainfed (temporal out of sample) | 1941 | 87.4% | 0.647 | 0.590 |
| All rainfed data 1977–2001 | 1997–2001 | Rainfed (training data) | 1941 | 84.2% | 0.897 | 0.906 |
| All rainfed data 1977–2001 | 1977–2001 | Irrigated (completely out of sample) | 444 | 72.1% | 0.950 | 0.918 |

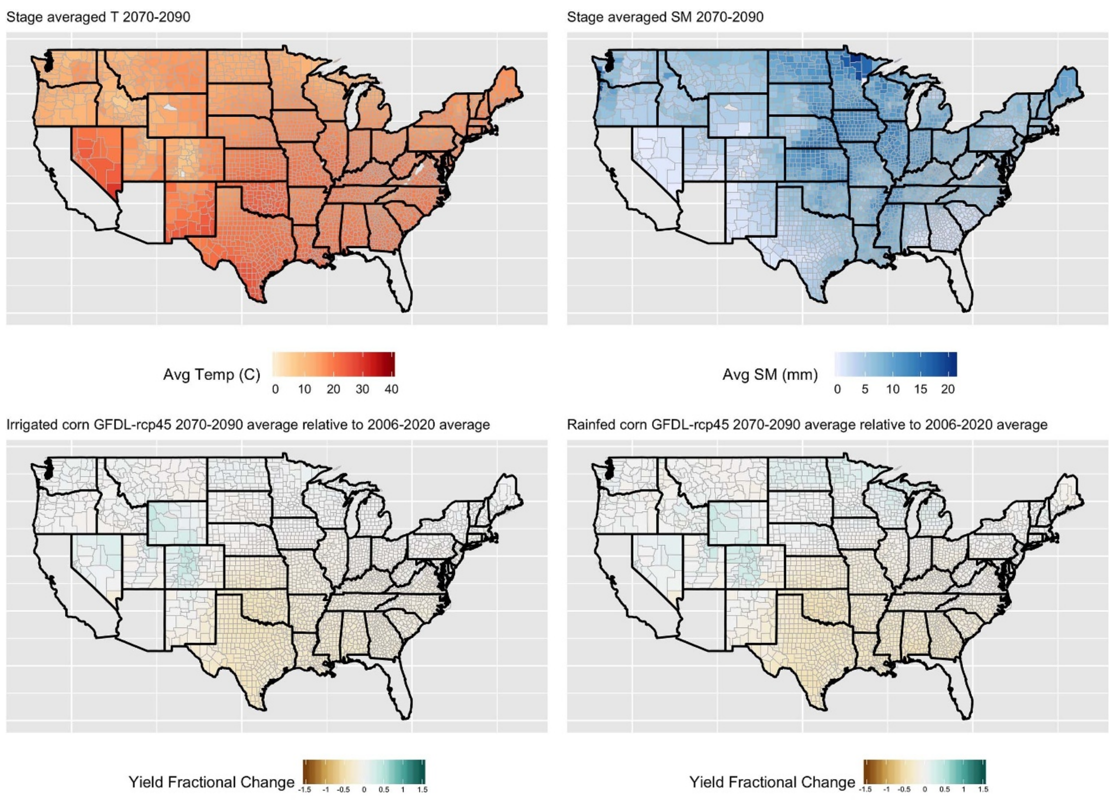


**Figure 5.** Irrigated and rainfed average annual weather shock projections from 2070–2090 relative to 2006–2020 average for GFDL RCP4.5. Top left: average temperature in all relevant growing stages from 2070 to 2090 as an aggregate visual aid. Top right: average soil moisture in all relevant growing stages from 2070 to 2090 as an aggregate visual aid. Bottom left: rainfed weather impact averaged across 2070–2090, relative to 2006–2020. Bottom right: irrigated weather impact averaged across 2070–2090, relative to 2006–2020.

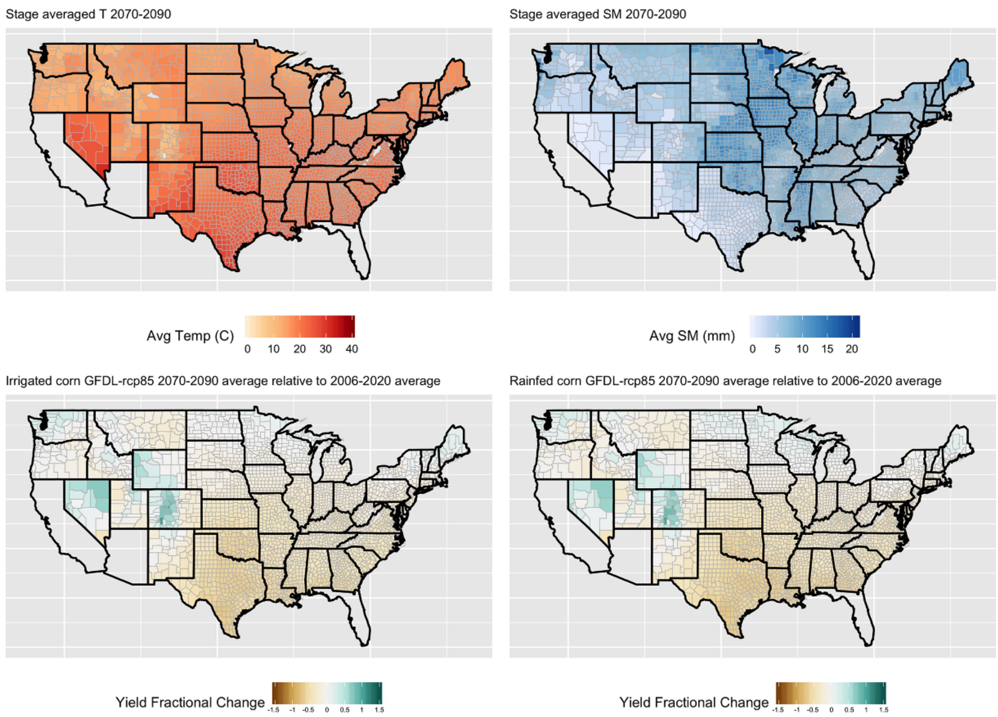


**Figure 6.** Irrigated and rainfed average annual weather shock projections from 2070–2090 relative to 2006–2020 average for GFDL RCP8.5. Top left: average temperature in all relevant growing stages from 2070 to 2090 as an aggregate visual aid. Top right: average soil moisture in all relevant growing stages from 2070 to 2090 as an aggregate visual aid. Bottom left: rainfed weather impact averaged across 2070–2090, relative to 2006–2020. Bottom right: irrigated weather impact averaged across 2070–2090, relative to 2006–2020.

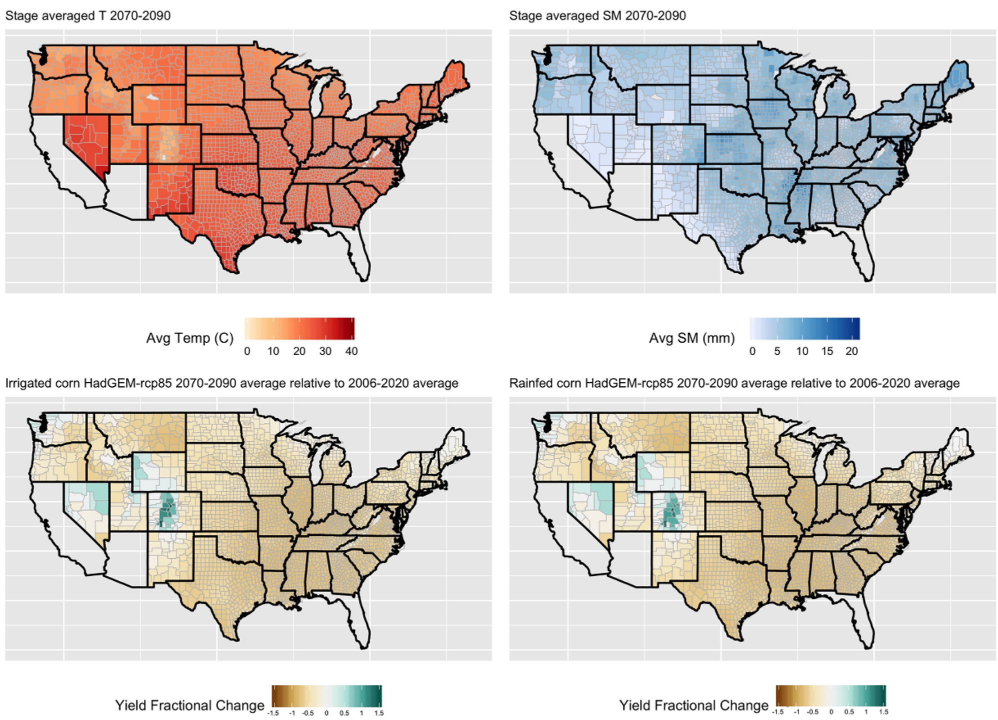


**Figure 7.** Irrigated and rainfed average annual weather shock projections from 2070–2090 relative to 2006–2020 average for HadGEM RCP8.5. Top left: average temperature in all relevant growing stages from 2070 to 2090 as an aggregate visual aid. Top right: average soil moisture in all relevant growing stages from 2070 to 2090 as an aggregate visual aid. Bottom left: rainfed weather impact averaged across 2070–2090, relative to 2006–2020. Bottom right: irrigated weather impact averaged across 2070–2090, relative to 2006–2020.

**Table 6.** Range of weather impacts across counties for U.S. maize yields. The average impact is not weighted, as we are attempting to present the average impact seen in each individual county rather than the U.S. average impact. Values in parentheses are standard deviations.

| Scenario | Irr/Rfd | Time period | Range | Average impact in a county |
|---|---|---|---|---|
| GFDL RCP 4.5 | Irrigated | 2040–2060 | −40.7% to +43.1% | −10.0% (±11.8%) |
| | Rainfed | 2040–2060 | −43.8% to +36.7% | −13.1% (±13.5%) |
| | Irrigated | 2070–2090 | −50.7% to +47.7% | −13.3% (±15.4%) |
| | Rainfed | 2070–2090 | −53.4% to +50.7% | −14.9% (±18.7%) |
| GFDL RCP 8.5 | Irrigated | 2040–2060 | −42.6% to +51.9% | −13.4% (±13.8%) |
| | Rainfed | 2040–2060 | −50.3% to +41.6% | −16.9% (±16.9%) |
| | Irrigated | 2070–2090 | −73.5% to +104% | −28.8% (±25.7%) |
| | Rainfed | 2070–2090 | −76.0% to +101% | −30.3% (±26.9%) |
| HadGEM RCP4.5 | Irrigated | 2040–2060 | −45.3% to +44.4% | −20.0% (±15.1%) |
| | Rainfed | 2040–2060 | −42.9% to +48.6% | −20.1%(±15.1%) |
| | Irrigated | 2070–2090 | −70.2% to +115% | −21.1% (±20.1%) |
| | Rainfed | 2070–2090 | −77.2% to +111% | −17.6% (±21. 5%) |
| HadGEM RCP 8.5 | Irrigated | 2040–2060 | −73.4% to +80.8% | −34.4% (±24.7%) |
| | Rainfed | 2040–2060 | −75.9% to +63.2% | −37.7% (±25.4%) |
| | Irrigated | 2070–2090 | −85.2% to +174% | −56.7% (±28.3%) |
| | Rainfed | 2070–2090 | −87.0% to +151% | −58.6% (±27.8%) |

**Table 7.** Range of weather impacts across counties for U.S. soybean yields. The average impact is not weighted, as we are attempting to present the average impact seen in each individual county rather than the U.S. average impact. Values in parentheses are standard deviations.

| Scenario | Irr/Rfd | Time period | Range | Average impact in a county |
|---|---|---|---|---|
| GFDL RCP 4.5 | Irrigated | 2040–2060 | −33.4% to +11.0% | −11.1% (±8.7%) |
| | Rainfed | 2040–2060 | −34.0% to +10.3% | −11.4% (±8.6%) |
| | Irrigated | 2070–2090 | −39.8% to +10.7% | −13.6% (±9.9%) |
| | Rainfed | 2070–2090 | −39.8% to +10.3% | −13.8% (±9.9%) |
| GFDL RCP 8.5 | Irrigated | 2040–2060 | −53.8% to +17.7% | −18.4% (±12.5%) |
| | Rainfed | 2040–2060 | −54.0% to +16.1% | −19.1% (±12.4%) |
| | Irrigated | 2070–2090 | −66.8% to +35.4% | −32.3% (±19.8%) |
| | Rainfed | 2070–2090 | −67.1% to +34.8% | −33.1% (±19.8%) |
| HadGEM RCP4.5 | Irrigated | 2040–2060 | −38.5% to +19.0% | −22.3% (±11.2%) |
| | Rainfed | 2040–2060 | −38.4% to +19.0% | −22.7% (±11.1%) |
| | Irrigated | 2070–2090 | −46.0% to +32.7% | −16.4% (±11.5%) |
| | Rainfed | 2070–2090 | −45.8% to +32.8% | −16.2% (±11.5%) |
| HadGEM RCP 8.5 | Irrigated | 2040–2060 | −72.3% to +21.5% | −36.8% (±17.5%) |
| | Rainfed | 2040–2060 | −73.0% to +20.6% | −37.5% (±17.4%) |
| | Irrigated | 2070–2090 | −80.8% to +22.5% | −60.7% (±15.0%) |
| | Rainfed | 2070–2090 | −81.1% to +22.2% | −61.0% (±15.0%) |

**Table 8.** Range of weather impacts across counties for U.S. winter wheat yields. The average impact is not weighted, as we are attempting to present the average impact seen in each individual county rather than the U.S. average impact. Values in parentheses are standard deviations.

| Scenario | Irr/Rfd | Time period | Range | Average impact in a county |
|---|---|---|---|---|
| GFDL RCP 4.5 | Irrigated | 2040–2060 | −5.7% to +6.2% | −1.5% (±1.6%) |
| | Rainfed | 2040–2060 | −9.5% to +4.6% | −3.7% (±2.3%) |
| | Irrigated | 2070–2090 | −5.0% to +3.1% | −2.6% (±1.3%) |
| | Rainfed | 2070–2090 | −8.5% to +4.0% | −4.1% (±2.1%) |
| GFDL RCP 8.5 | Irrigated | 2040–2060 | −6.6% to +5.7% | −2.0% (±1.5%) |
| | Rainfed | 2040–2060 | −9.9% to +4.1% | −4.0% (±2.4%) |
| | Irrigated | 2070–2090 | −11.8% to +2.1% | −5.2% (±2.2%) |
| | Rainfed | 2070–2090 | −15.5% to +4.7% | −6.5% (±3.5%) |
| HadGEM RCP4.5 | Irrigated | 2040–2060 | −9.8% to +4.3% | −4.4% (±2.2%) |
| | Rainfed | 2040–2060 | −13.9% to +5.2% | −6.0% (±3.1%) |
| | Irrigated | 2070–2090 | −17.3% to +3.8% | −7.7% (±3.2%) |
| | Rainfed | 2070–2090 | −18.1% to +12.3% | −6.2% (±4.1%) |
| HadGEM RCP 8.5 | Irrigated | 2040–2060 | −10.0% to +1.4% | −4.8% (±1.7%) |
| | Rainfed | 2040–2060 | −13.9% to +1.0% | −7.5% (±2.4%) |
| | Irrigated | 2070–2090 | −15.0% to −2.1% | −10.0% (±1.9%) |
| | Rainfed | 2070–2090 | −17.8% to −3.3% | −11.6% (±2.3%) |

## 5. Conclusions

This work presents a novel approach to future projections of weather-induced changes to U.S. rainfed and irrigated crop yields, utilizing a structural econometric approach based on key biophysical growth stages and considering collinearities among time, $CO_2$ concentrations, temperature, and GDP *per capita* seen in the historical data.

By assuming that irrigation achieves the soil moisture levels that maximize yields, we are able to apply our rainfed model to irrigated data with success. Given that rainfed data is available for far more counties than irrigated, this results in a more spatially applicable yield response than if an irrigated model was developed from data using currently irrigated areas alone. We also provide results for soybeans and winter wheat, with similar levels of confidence in the model fit. The fitted models of weather-only shocks (equation (3)) are applied to projections of weather data under four GCM-RCP scenarios to develop projections of annual yield shocks for irrigated and rainfed maize, winter wheat, and soybean at the U.S. county-level.

There remain limitations to both the current work and possible future extensions of this approach. Two areas with which this empirical approach is fundamentally limited include the responses of yields to large changes in $CO_2$ concentration and the development of crop cultivars (such as more drought-resistant varieties) or other adaptation measures beyond irrigation that may be developed in the future. For experiments requiring future projections, the methods presented in this work could be used with different proposed crop calendars, allowing for a scenario-based exploration of that adaptation dimension. Although we do find poorer performance in counties with smaller harvested areas, it is of less importance for using these weather-driven yield impacts in economic models, as the effects on yields in counties with larger harvested areas have more of an impact on production and prices than counties with small harvested areas. For extensions of this work to additional crops and to regions outside of the United States, data availability is a major future challenge. While the United Nations Food and Agriculture Organization collects yield information globally, they are only available at country-levels and combine irrigated and rainfed yields into one value. Extensions of this method could be adapted to the scale of United Nations Food and Agriculture Organization (FAO) data. A robust exploration of sensitivity to the uncertainties in soil moisture estimates would be another avenue for future work. This work addressed such uncertainties by using a validated hydrology model driven by bias-corrected data to provide soil moisture values (Xanthos) and by the consistent use of that model between the historical training period and the future projection period to avoid the introduction of new errors.

This work empirically estimates future projections of weather-only changes for rainfed versus irrigated crops in a single model that is appropriate for ingestion by economic models with more aggregate spatial scales. Using biophysically relevant growth stages allows data from regions with different timing and length of growing season to be used to develop a single model to identify intrinsic weather-only responses of the crop being grown. The use of biophysically relevant growth stages also allows for the timing of weather events to impact modeled yields more realistically than in models relying on annual or growing season maximum, minimum, and mean weather data. Finally, the methods described here enable prediction of the potential impacts of changing weather patterns on irrigated crops in areas that are currently primarily rainfed, which downstream economic models require in order to project the use of irrigation as an adaptive response to changing weather conditions. This projections of annual yield shocks developed in this work provide a valuable input to modelers to understand the potential future crop yield responses to changing temperature and soil moisture conditions, particularly the use of irrigation as an adaptation response.

## Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: 10.5281/zenodo.4022805. Data will be available from 10 September 2021.

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