Supplementary Material for

Stochastically modeling the projected impacts of climate change on rainfed and irrigated US crop yields

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The supplementary material in this document provides more details about the model structure and its cross validation to supplement the main text.
1. Model Details

The statistical regression model was developed to simulate crop yield response to climate conditions, including interannual variability and extremes, for each crop’s growing region for both rainfed and irrigated states. The regression model was fit using historical climate indices and then applied using CMIP5 projections. Before applying it to the projections, the ability of the CMIP5 models to simulate the probability distributions of the climate indices over the growing regions for the growing season was evaluated.

1.1 Predictor choice

We considered 23 agriculturally relevant climate indices (Table 1, taken from Zhu and Troy, 2018 and references therein) to include as potential predictors in our model. These indices were calculated for the growing seasons of four crops (maize, soybean, spring wheat, and winter wheat). To select the predictors, stepwise regression was performed. First, for each county in each growing region (Figure 1), univariate linear regression was run between the times series of county-level detrended crop yields and each of the 23 standardized climate indices. This procedure returned 23 R-squared values in total, associated with the regression involving 23 indices. Whichever index returned the largest R-squared was then chosen as the first predictor. We kept the first predictor and added each of the other 22 indices and ran the regression, resulting in 22 new adjusted R-squared values. Whichever combination had the largest adjusted R-squared was chosen. Similarly, we kept the two predictors already chosen and added each of the other 21 indices and ran the regression, resulting in 21 new adjusted R-squared values. Whichever combination that returned the largest adjusted R-squared was chosen. By repeating this process, we obtained a combination of indices that returned the largest adjusted R-squared when regressed with the detrended crop yield time series. The stepwise regression was terminated when adding another variable did not result in at least a 0.01 increase in adjusted R-squared, indicating the model performance is relatively unchanged. Finally, we obtained combinations of climate indices as predictors unique by crop, county, and irrigated state (Table 2, main text). There is one exception to this approach. For rainfed maize, GDD and HD30 are highly correlated, and the model selected HD30. However, GDD is known as a significant predictor of crop growth, so this variable was forced to be a predictor.

The regressions described above, performed for each county within a growing region for both irrigated and rainfed agriculture, result in a set of potential predictor choices, varying by county, for a growing region. To have a growing region-level set of climate predictors, we ran multivariate linear regression between the county-level detrended crop yields (time window of seven years) and the predictor combinations chosen for this county and the other counties in this growing region. For instance, there are 125 counties growing irrigated maize. From the county-level stepwise regression, we obtained 125 combinations of possible final predictors associated with each county, acknowledging that some predictor combinations may repeat across counties. Then for each of the 125 counties, we applied each of the 125 combinations and ran multivariate linear regression using county-level detrended crop yields and standardized predictors. This process eventually returned $125 \times 125$ adjusted R-squared values. Next, we calculated the average adjusted R-squared for each combination of predictors across the growing region, providing us with 125 mean adjusted R-squared as a result. Whichever combination that is associated with the largest mean adjusted R-squared was chosen as the final combination for that growing region (Table 2).
1.2 Regional pooling and model implementation

After finalizing the combination of predictors, we performed multivariate linear regression between the county-level detrended crop yields and chosen predictors for each county within the growing region, which results in deterministic regression coefficients for each predictor by county. Then, for each predictor in the final combination, we regionally pooled their county-level deterministic coefficients and fit probability distributions to these coefficients. If it passed the Kolmogorov–Smirnov test, a normal distribution was used, otherwise we fit kernel density to the pooled regression coefficients fitting (Figures S1-S10).

![Probability density function (PDF) of fitted distributions associated with different predictors for irrigated maize.](image)

**Figure S1.** Probability density function (PDF) of fitted distributions associated with different predictors for irrigated maize.
Figure S2. PDF of fitted distributions associated with different predictors for rainfed maize.

Figure S3. PDF of fitted distributions associated with different predictors for irrigated soybean.

Figure S4. PDF of fitted distributions associated with different predictors for rainfed soybean.
Figure S5. PDF of fitted distributions associated with different predictors for irrigated spring wheat.

Figure S6. PDF of fitted distributions associated with different predictors for rainfed spring wheat.
Figure S7. PDF of fitted distributions associated with different predictors for irrigated winter wheat in the Northwest.

Figure S8. Probability Density Function (PDF) of fitted distributions associated with different predictors for rainfed winter wheat in the Northwest.
Figure S9. PDF of fitted distributions associated with different predictors for irrigated winter wheat in the South.

Figure S10. PDF of fitted distributions associated with different predictors for rainfed winter wheat in the South.

Pooling coefficients accounts for a range of crop yield responses to climate. During each model run, we stochastically sampled coefficients associated with the first chosen predictor $Index_1$ in each combination from the corresponding fitted distribution. Then we found the nearest neighbor associated with the sampled coefficient in deterministic $Index_1$ values. This deterministic $Index_1$ value along with the associated deterministic values of other predictors in this combination were
also chosen. Similarly, we did the process starting with sampling $Index_2$, $Index_3$, etc. This process allows for the range of yield response while accounting for the correlation between climate indices and their coefficients.

For the model validation process, we used standardized historical predictors and the sampled coefficients to simulate historical detrended crop yields. The mean $R^2$ values across counties were calculated using median simulated detrended crop yields and historical detrended crop yields to quantify model performance (Table S1). For the crop yield projections, we first compared historical predictors from Maurer et al (2002) and five different downscaled CMIP5 climate models (Brekke et al 2013). In general, we found that these models could simulate the distribution of historical predictors for 1970-2010 (Figures S11-S15). For future simulations, we ran the model with the standardized predictors from the climate projections. During each run, 10,000 Monte-Carlo simulations were performed with sampled coefficients.

| Mean $R^2$ values | Crops          | Maize | Soybean | Spring Wheat | Winter Wheat (Northwest) | Winter Wheat (South) |
|-------------------|----------------|-------|---------|--------------|--------------------------|----------------------|
| Irrigated Only    | 0.4207         | 0.4464| 0.2923  | 0.4096       | 0.4631                   |
| Rainfed Only      | 0.5486         | 0.5401| 0.4227  | 0.4617       | 0.5040                   |

Table S1. Mean $R^2$ values obtained from the model during the historical period.

 Counties with less than 30 years of data were not used to fit the regression coefficients because it could result in an overfitted model. Less than 30 years of data may not adequately capture the crop response to climate, as it would not have a sufficiently long time series to ensure there are both wet and dry periods and hot and cold periods. We chose to include the counties with at least 10 years of data for the projections for two reasons. First, we know that these crops were grown in these regions and wanted to characterize the impacts of climate there. Second, this was possible because we could validate the model using the shorter time period. By choosing to include counties with at least 10 years of data, this is a sufficiently long time period to allow for the validation of the model to have confidence that it can be applied there. The mean $R^2$ values obtained during validation of those added counties with $N>=10$ are shown below (Table S2). Compared to the final mean $R^2$ values obtained from the model (Table S1), the changes in $R^2$ values were less than 0.05.
| Mean R squared values | Crops | Maize | Soybean | Spring Wheat | Winter Wheat (Northwest) | Winter Wheat (South) |
|-----------------------|-------|-------|---------|--------------|-------------------------|---------------------|
| Irrigated Only        | 0.4021| 0.3965| 0.2806  | 0.3928       | 0.4421                  |
| Rainfed Only          | 0.5093| 0.4973| 0.4169  | 0.4370       | 0.4894                  |

Table S2. Mean R squared values obtained from the model during validation of added counties with N>=10.

Figure S11. Comparison of probability density function of historical predictors between Maurer data and five CMIP5 climate projections for maize.
Figure S12. Comparison of probability density function of historical predictors between Maurer data and five CMIP5 climate projections for soybean.

Figure S13. Comparison of probability density function of historical predictors between Maurer data and five CMIP5 climate projections for spring wheat.
Figure S14. Comparison of probability density function of historical predictors between Maurer data and five CMIP5 climate projections for winter wheat (Northwest).

Figure S15. Comparison of probability density function of historical predictors between Maurer data and five CMIP5 climate projections for winter wheat (South).

2. Cross Validation Statistics

We did ten cross validations to evaluate our statistical model. During each cross validation, a random thirty years were used to first build the model. Then we used the other ten years of historical yields to validate the model performance. The R squared values were calculated using median simulated and historical detrended crop yields across counties. The difference in mean R
squared values between each pair of ten cross validations was less than 0.01. Table S3 shows the average of mean R squared values calculated from all cross validations. This result was similar to the R squared values in Table S1, as R squared changes were less than 0.02. The results also showed that different historical data for the model setup did not result in different model performance.

| Mean R squared values | Crops | Maize  | Soybean | Spring Wheat | Winter Wheat (Northwest) | Winter Wheat (South) |
|-----------------------|-------|--------|---------|--------------|--------------------------|----------------------|
| Irrigated Only        | 0.4152| 0.4259 | 0.2895  | 0.4002       | 0.4520                   |                      |
| Rainfed Only          | 0.5164| 0.5318 | 0.4117  | 0.4581       | 0.4943                   |                      |

Table S3. Mean R squared values obtained from ten cross validations.

References:

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