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ARTICLE

Agricultural innovation and adaptation to climate change: Insights from US maize

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Abstract

Climate change is a major threat to the global food supply, and adaptation by technological progress is essential. We show that the scope of the required innovation is challenging. Our benchmark is the estimated yield gain in US maize due to genetically engineered (GE) varieties. Extrapolated future yields, given climate projections, indicate significant negative impacts of climate change. Yield shortfalls, by the end of the century, range from 2.8 to 6.3 times the total yield gains from first-generation GE varieties. Ambitious and targeted R&D efforts, and innovation breakthroughs, may be required to offset the negative impact of climate change.

KEYWORDS

adaptation, agricultural productivity, climate change, genetically engineered varieties, innovation, maize

JEL CLASSIFICATION

Q16, O47, C23

1 | INTRODUCTION

Production agriculture depends heavily on exogenous environmental conditions and is thus acutely vulnerable to the deleterious long-run effects of climate change. Mounting evidence suggests large negative impacts (Fisher et al., 2012; Mendelsohn et al., 1994), with severe adverse consequences for major staple crops' yields (S. Chen et al., 2016; Gammans et al., 2017; Lobell et al., 2011; Miller et al., 2021; Schlenker & Roberts, 2009; Tack et al., 2015). The long-run health of the food supply may thus need deliberate mitigation and/or adaptation measures to deal with global warming. First-best mitigation strategies aimed at containing climate change, chiefly by reducing greenhouse gas (GHG) emissions, are proving problematic, due to the global and dynamic nature of the externalities involved with climate change (Carattini et al., 2019). Adaptation strategies, to blunt and counteract the damaging consequences of climate change, are perhaps more promising because they are less vulnerable to such strategic problems—whereas GHG emission reduction is a global public good, investments in adaptation often have local payoffs and substantial private good aspects (Hasson et al., 2010; Tol, 2005).

Successful efforts to cope with a hostile environment are a major component of the history of agriculture (Olmstead & Rhode 2011). Technologies to foster agriculture's adaptation may include, inter alia, new crop varieties with traits enhancing their broad resistance to pest, disease, and environmental stress, particularly heat tolerance and resistance to drought and salinity (Lybbert & Sumner 2012). Varieties with shorter growing cycles and earlier maturation, precision agriculture technologies and more efficient water management, and expanded irrigation are also expected to be critical. Technological innovations beyond the farm level are also envisioned (Zilberman et al., 2018), including institutional innovation with a focus on adoption incentives and an appreciation for the role of learning, networks, and social capital (Zilberman et al., 2012). Ultimately, all this requires major R&D investments, from both the public and private sectors, to support enhanced innovation efforts in adaptation-enabling new technologies.

What is the scope of such an R&D challenge? Harnessing the potential of modern biotechnology, beyond traditional breeding, is obviously critical in this setting. Hence, we propose to gauge the extent of innovation required to offset the impact of climate change on yields by using first-generation genetically engineered (GE) varieties in US maize production as a "yardstick." Specifically, we estimate the contribution of GE traits separate from the long-run productivity improvements that have characterized maize yields with the diffusion of hybrid varieties. The estimated model, along with weather projections from mainstream climate change models, permits us to forecast expected yields at mid-century and end-of-century and thus characterize the ceteris paribus yield shortfalls due to anticipated climate change. Comparison of such yield effects with the one-time yield gains due to first-generation GE traits in maize provides a useful metric for the innovation challenge posed by climate change.

First commercialized in 1996, GE seeds rapidly replaced conventional varieties. In maize, commercially successful first-generation GE varieties have embedded agronomic traits—herbicide tolerance (HT), chiefly tolerance to glyphosate (aka Roundup), and insect resistance (IR), specifically resistance to the European corn borer and corn rootworms. Farmers' keen interest in GE adoption attests to their perceived profitability. Experimental evidence also points to a significantly positive impact of GE on maize yields (Chavas et al., 2014; Nolan and Santos, 2012), and observational data on realized yields also shows a clear positive impact (Lusk et al., 2019; Xu et al., 2013).

To characterize the impact of GE maize varieties on yield, we use a panel of county-level yield data. Our approach improves on previous work by a somewhat more nuanced measurement of maize GE adoption rates, and by an explicit representation of the interaction effects between GE adoption and weather variables. Similar to previous work, our yield model is estimated conditional on historical weather metrics based on daily temperature and precipitation from the Parameter-elevation Regressions on Independent Slopes Model (PRISM). The estimated model is used for counterfactual simulations to determine the expected yield impacts of anticipated climate change, using weather projections from all 20 global climate models (GCMs) from the Multivariate Adaptive Constructed Analogs (MACA) data set (Abatzoglou & Brown, 2012). Mid-century (2040–2059) and end-of-century (2080–2099) weather predictions and future climate conditions are used to compare scenarios under two GHG concentration pathways.

Our results confirm the finding of previous studies that GE varieties have led to significant productivity gains in maize production. Accounting for weather conditions is essential to identify the role of technology in maize production—yields are significantly positively impacted by growing degree days, are negatively impacted by excess heat, and are sensitive to precipitation and water stress. We find sizeable yield shortfalls due to the changing weather predicted by these GCMs. Depending on GHG concentration pathways, average yield shortfalls due to climate change at mid-century range from 2.0 to 2.7 times the entire yield gains made possible by the adoption of GE varieties. By the end of the century, the estimated average yield gaps range from 2.9 to 6.3 times the GE yield gain.

To put these results in context, it is important to appreciate that GE crop varieties were developed in the 1980s from the application of revolutionary recombinant DNA techniques discovered in the 1970s (Bennett et al., 2013; Moschini, 2008). The commercialization, and eventual widespread adoption of GE varieties in maize, soybeans, and cotton, was made possible by massive R&D investments, mostly by the private sector. In the process, the company leading this development, Monsanto, radically transformed itself from a chemical business to the largest seed company in the world (Clancy & Moschini, 2017). Finding that yield gains several times larger than what was accomplished with first-generation maize GE varieties are needed, to offset the likely impacts of global climate change, underscores the challenging scope of the required R&D enterprise.

2 | DATA

The main variable to be explained is the US maize yield (bushel/acre) at the county level. Similar to other studies in this area, the focus is on rainfed agriculture. Specifically, as in Xu et al. (2013), counties are included in the sample if the fraction of harvested cropland that is irrigated is less than 10% (based on the USDA census of 2002). Furthermore, the analysis is limited to data since 1981, as in Ortiz-Bobea and Tack (2018), to ensure that daily precipitation and temperature data are available. We draw on county-level maize yield data from the USDA-NASS for the period from 1981 to 2020. Our sample includes 1774 counties across 36 states. Note that NASS does not provide maize production and yield data for all counties over the entire period of interest—some marginal counties may not appear in some years. On average, 1510 counties are observed per year. Hence, the final data we end up using in estimation has the nature of an unbalanced panel (a total of 60,400 panel observations over the entire period). Figures A1 and A4 in the Supporting Information Appendix illustrate the geographic area of our analysis and the spatial and temporal variations of observed yields.

As for GE adoption, in this paper, we exploit a more refined measure of GE adoption rates than used by previous studies. The USDA survey-based state-level GE adoption data used by previous studies have two drawbacks: they are available only starting in the year 2000, thereby missing the crucial early years of GE diffusion, and they cover only a limited number of large maize-growing states. Our adoption data are largely constructed from an extensive set of farm-level observations of seed choices by US maize farmers assembled by Kynetec USA, a market research organization that collects agriculture-related survey data. These proprietary data are based on annual surveys of random, large samples of US farmers (approximately 4700 maize farmers every year). These data are available to us from 1996 to 2016, thereby encompassing the entire period from the introduction of GE traits to their virtually complete adoption. Details on data handling are provided in the Supporting Information Appendix. For the last 4 years of analysis, Kynetec data are supplemented with USDA data, without much loss of generality because adoption in the last few years has been stationary. Based on these data, we are able to construct reliable adoption rates for 21 states. The pattern of spatial and temporal variation of GE adoption rates is illustrated in Figures A2-A3 in the Supporting Information Appendix. Adoption rates are spatially heterogeneous, especially in the first half of the adoption period, but this variability is reduced with adoption rates converging to more than 90% in the last few years.

As for weather data, daily temperature and precipitation are procured from the 4 km by 4 km grid cell PRISM data set. The county-level temperature and precipitation variables are obtained via an area-weighted scheme (Sacks et al., 2010). Two standard metrics of heat used in modeling crop yields are growing degree days (GDD) and extreme heat degree days (HDD) (Roberts et al., 2013). Daily GDDs and HDDs are aggregated over the growing season—defined as the months March to

August, as in Schlenker and Roberts (2009) and Lusk et al. (2019)—to produce the annual measures of beneficial temperature and heat stress for the county in question.

To measure water stress, Schlenker and Roberts (2009) merely add the total volume of precipitation and its quadratic in the growing season, March through August. However, Roberts et al. (2013) find that the correlation between precipitation and yield is weak, and suggest that insufficient moisture can be better captured by additionally considering vapor pressure deficit (VPD). Hence, we use VPD along with cumulative precipitation to represent water stress. VPD relates to the difference between how much moisture the air can hold when saturated and the actual air moisture. It is related to relative humidity, but it additionally accounts for the effects of temperature on the water holding capacity of the air (Sinclair, 2011). When the actual air moisture is not observed, it can be approximated by using the daily minimum temperature in lieu of the dew point. Similar to GDD and HDD, daily VPDs are aggregated over the growing season to form annual county-level measures. As in Roberts et al. (2013), we utilize two VPD metrics, the VPD for the March-August growing season, and the VPD for the July–August months only. Cumulative precipitation with its quadratic is also included in the model. Descriptive statistics for the main weather variables used in the analysis, and their spatial and temporal variation, are included in the Supporting Information Appendix (Table A2-A5 and Figure A5).

Because GCMs produce weather projections at coarse spatial cells, Auffhammer et al. (2013) highlighted the need for downscaling and bias correction. In this paper, we relied on a set of 20 downscaled and bias-corrected GCM projections available in the MACA data set. For each climate model (or set of models), future weather data are obtained under two warming scenarios defined by the GHG representative concentration pathways (RCP), specifically RCP 4.5 and RCP 8.5. Forecasted temperature and precipitation for the years 2040 to 2059 are used to generate weather variables at mid-century climatic conditions, and, correspondingly, forecasts for the years 2080 to 2099 are used to generate end-of-century weather data. Consistent with the discussion in Burke et al. (2015), we use model-implied temperature and precipitation for all periods when calculating the difference in weather variables between the historical period and future periods. Specifically, the weather variables for the stationary climate scenarios are assumed to be the model-implied estimates over the period 1981–2005 (climate models provide current modeled temperature and precipitation only through 2005). Summary statistics of the predicted weather variables for the reference historical period and the two future periods (mid- and end-century), obtained from the 20 GCMs considered, are included in the Supporting Information Appendix.

3 | YIELD RESPONSE MODEL

The model to be estimated postulates that observed (realized, end-of-season) county maize yields (production per acre) are determined, inter alia, by the technology of production and realized climatic conditions (weather). We are particularly interested in separating the one-time impact of GE trait adoption from the underlying continuous technical progress due to all other improvements/breeding activities. The models we estimate can be written as:

$$y_{it} = \alpha_i + \mathbf{X}_{it}\boldsymbol{\beta} + \gamma G_{st} + G_{st}\mathbf{X}_{it}\boldsymbol{\delta} + \tau_s T_t + \varepsilon_{it}, \tag{1}$$

where i is county index; t indicates year; s indicates the state of county i; the conditioning (row) vector $\mathbf{X}_{it}$ includes all the weather variables of interest, discussed earlier; G_{st} is the GE adoption rate (measured, as noted, at the state level); and, $T_t = 1, 2, \ldots, 40$ is the linear trend variable. The parameter vector $\boldsymbol{\delta}$ captures the interaction effects between GE adoption and weather variables. Note that the trend coefficient τ_s, meant to capture the underlying technical change beyond that embedded in GE traits, is allowed to vary at the state level. Finally, the intercept α_i is county-specific and captures heterogeneous factors impacting yield (e.g., soil quality) that are unobserved but largely time-invariant.

The parameterization of the GE trait effect in (1) maintains what Xu et al. (2013) call the "adoption shift" model—full adoption of GE traits leads to a one-time shift in the yield trajectory. Alternatively, one could postulate that GE trait adoption changes the trend slope, which is presumed to reflect the overall impact of technical change. The "adoption slope" model is virtually indistinguishable, in sample, from the shift model (Lee et al., 2022). For mid-century and end-century projections, however, it would produce larger effects the further away in the future. We submit that the adoption shift model is both more conservative and more appropriate for our analysis. In particular, we are not interested in projecting the unconditional impacts of current and future GE technologies. Rather, we merely wish to use yield gain attributable to GE traits as a yardstick. This benchmark is not meant to capture all future productive impacts of GE technologies, but rather the realized yield effects of hitherto-adopted first-generation GE varieties embedding agronomic traits.

Two issues need to be addressed to make the model in Equation (1) operational. One concerns the representation of GE adoption rates. As discussed earlier, both HT and IR traits have been introduced into maize varieties, alone or in combination, and at different times. It is likely that HT and IR traits affect yield differently.[1] As illustrated in the Supporting Information Appendix, however, HT and IR traits have been jointly adopted via stacked traits, which makes it difficult to credibly identify the separate contributions of the two types of traits. Similar to previous studies, we represent the impact of GE through a single adoption variable.

The second issue to be resolved concerns the representation of the left-hand side of Equation (1). Many studies in this area have adopted a "semi-log" functional form. That is if Y_{it} denotes the actual yield (bushels per acre), then $y_{it} \equiv \ln Y_{it}$ (e.g., Burke & Emerick, 2016; Malikov et al., 2020; Ortiz-Bobea & Tack, 2018; Schlenker & Roberts, 2009; Roberts et al., 2013). Alternatively, others have assumed a fully "linear" functional form; that is, $y_{it} \equiv Y_{it}$ (e.g., Lusk et al., 2019; Nolan & Santos, 2012; Xu et al., 2013). The choice between the linear and semi-log models can be cast in terms of the LHS transformation analyzed in the seminal paper by Box and Cox (1964). Results reported in the Supporting Infomation Appendix (Table A6) overwhelmingly favor the linear model relative to the (widely used) semi-log model. Based on these results, we focus on the linear formulation for the remainder of the paper.

Identification of the GE and trend impacts as modeled by Equation (1) relies on the temporal and spatial variation in the adoption of GE varieties (Lusk et al., 2019; Xu et al., 2013). The crux of the argument is that the timing of commercialization of specific GE varieties is largely exogenous—see the related extensive discussion presented in Ciliberto et al. (2019). Other sources of productivity growth, such as continuing germplasm improvement by conventional breeding, is also traditionally taken as exogenous to farmers' decisions, and the model captures that by a linear trend. The fact that the GE adoption was technologically constrained to zero up to 1996 helps with the identification of GE effects, separate from other sources of yield growth that presumably operated throughout the sample period. Furthermore, we recognize that the latter may operate differently under dissimilar growing conditions, and the model permits trends to differ across states. Other confounding factors, beyond the weather effects that we explicitly model (such as pest pressure differing across regions), are assumed to be accounted for by country-specific fixed effects.

We note at this juncture that the objective of this paper is close in spirit to Ortiz-Bobea and Tack (2018). Differences in modeling choices that bear on the interpretation of the results, however, are worth noting. They do not use the information on the (gradual) adoption of GE varieties, and instead rely on the timing of GE crop introduction, identifying the GE effect on yield by the difference between the slopes from piecewise linear trend segments, before and after the initial 1996 commercialization of the GE technology. By contrast, we explicitly introduce the adoption rates in the model and represent this effect as an additive factor. This maintains that the gains from the

[1]GE traits conferring insect resistance provided a novel technology to control infestations, such as those by the European corn borer, that had hitherto been only partially treated. By contrast, GT traits simply provided a new (cost-effective) avenue to weed control that, however, had already been effectively managed with alternative herbicides. The large body of experimental evidence analyzed by Nolan and Santos (2012) indicates strong yield effects from IR traits, and essentially no impact of HT on maize yield.

TABLE 1 Estimated yield model, 1981–2020 (36 states)

	Model 1			Model 2		
	Coefficient	**SE**	***p* Value**	**Coefficient**	**SE**	***p* Value**
GE	16.60	0.533	0.000	14.22	0.528	0.000
GDD	0.0120	0.0012	0.000	0.0144	0.00129	0.000
HDD	−0.316	0.009	0.000	−0.293	0.0102	0.000
VPD	3.396	1.338	0.011	10.47	1.399	0.000
VPD, July–Aug	−29.13	0.619	0.000	−27.22	0.704	0.000
PPT	0.0510	0.00327	0.000	0.0814	0.00442	0.000
PPTsq	−0.0000485	2.61E−06	0.000	−0.0000799	3.85E−06	0.000
GE × GDD				0.000647	0.00163	0.691
GE × HDD				0.0286	0.0195	0.143
GE × VPD				−13.75	2.602	0.000
GE × VPD, July–Aug				−12.93	1.597	0.000
GE × PPT				−0.0110	0.00837	0.190
GE × PPTsq				0.0000252	6.59E−06	0.000
Avg. time trend	0.826	0.105	0.000	0.945	0.102	0.000
State-specific trend:						
Illinois	1.320	0.0296	0.000	1.300	0.0292	0.000
Indiana	1.208	0.0287	0.000	1.157	0.0288	0.000
Iowa	1.520	0.0282	0.000	1.433	0.0283	0.000
Constant	86.31	0.205	0.000	85.56	0.206	0.000
Adj. R^2	0.776			0.782		
N	60,400			60,400		

Note: All weather variables are demeaned so as to have a mean of zero over the estimation sample, such that the effect of the coefficient of the GE variable is directly comparable between Models 1 and 2 (which includes interaction effects).

Abbreviations: GE, genetically engineered; HDD, extreme heat degree days; GDD, growing degree days; VPD, vapor pressure deficit.

adoption of these first-generation agronomic GE traits is a one-time occurrence (notwithstanding the fact that genetic engineering, going forward, may be essential to sustain the trajectory of productivity gains captured by the underlying linear trend).

4 | ESTIMATION RESULTS

Results for the GE effect on maize yield from the historical data from 1981 to 2020 are reported in Table 1.[2] In this table Models 1 and 2 are defined in Equation (1) when, respectively, the interaction effects between GE adoption and weather variables are not and are included. It is apparent that conditioning yield response by realized weather variables is crucial. The *F* statistics of the null

[2]Estimation of the panel data model relies on the REGHDFE module in Stata (Correia, 2019).

hypothesis that the coefficients for all weather variables are jointly equal to zero is, respectively, $\hat{F}(658, 583) = 2456.0$ for Model 1 (no interaction effects) and $\hat{F}(12, 58, 577) = 1349.5$ for Model 2. It is apparent that the null of no weather impacts is conclusively rejected ($p < 0.0001$ in all cases). The GE-weather interaction effects included in Model 2 are also significantly different from zero in their own: the F statistics is $\hat{F}(658, 577) = 174.62$. Consistent with previous research results, for all models reported in Table 1, we find that the GDD variable has a positive and significant impact on yields, whereas heat stress, captured by the HDD variable, has a negative and significant impact.

Our inferences, here and in what follows, are based on the so-called Huber-White covariance that is robust to heteroscedasticity (White, 1980). The question that naturally arises in this setting is whether concerns about the nature of the panel data at hand (arising, e.g., from correlated weather across counties in the same state, or from the use of state-level adoption rates for GE traits), should suggest the use of clustered standard errors. As discussed by Abadie et al. (2017), much of the conventional wisdom on this matter appears misplaced. We provide additional discussion of this matter in the Supporting Information Appendix, where we also report the results of a few alternative clustering strategies (Table A7).

Water stress matters as well, in a substantial way. Yield response to precipitation is (predictably) concave. As the model includes season-total VPD and July–August VPD separately, the effect of VPD on yield from July to August can be measured by summing the two coefficients. The positive coefficient of the season-total VPD implies a positive effect of VPD on yield in the early-to-middle growing season. For July and August, however, the corresponding VPD coefficient is negative and much larger than that of the season-long variable, indicating an overall negative impact of VPD on yield. This is consistent with evidence that water stress is particularly detrimental to yield during certain stages of crop development (Lobell et al., 2014; Ortiz-Bobea et al., 2019)—for maize, July and August are critical months for plant growth. Water stress coefficients are found to be highly statistically significant.

The effects of technology on maize output are large in magnitude and statistically significant. Model 2, the most general specification and our baseline parameterization, shows an average gain of 0.95 bushels per acre per year across all counties over the period 1981–2020 (this estimate is a simple average of estimated state-specific trend coefficients). State trend effects are quite heterogeneous—the *F*-test of the null hypothesis for the equality of state-specific trend coefficients gives a statistic of $\hat{F}(35, 58, 577) = 93.27$, clearly rejecting the null ($p < 0.0001$). For illustration, we also report the state-specific trend coefficients for the three states with the largest contribution to US maize production—Iowa, Illinois, and Indiana. Clearly, in these three corn-belt states, the annual yield gain from technological improvements captured by the time trend is much higher than in the rest of the country.

Model 1 suggests that the full adoption of GE traits, per se, contributes a one-time gain of about 16.6 bu./acre. This effect is large, equivalent to the gains of almost 20 years of underlying trend effects. Model 2, which accounts for the interaction effects of GE with weather variables, provides a slightly attenuated estimate. Note that all weather variables were demeaned (using the overall average over the historical period) to ensure that the coefficients of the GE variable are directly comparable between Models 1 and 2. From Table 1 it is apparent that the overall impact of allowing the interaction between weather and GE traits actually lowers the estimated GE effect, to 14.2 bu./acre (at full adoption of first-generation GE varieties). Thus, in this model, the GE effect is equivalent to about 16 years of the underlying trend effect.[3]

The estimated coefficients for the interaction GE-weather terms are suggestive of the potential effect of GE varieties under climate change. The interaction effect between GE and GDD is essentially nil. The interaction between GE adoption and the HDD variable suggests a moderate

[3]Our estimated GE effect is remarkably close to that inferred by Nolan and Santos (2012) who, with a very different methodology and data, estimated the yield gains for GE maize in the range of 13.3 and 14.8 bu./acre.

positive effect, with GE traits making maize yield more resilient to high temperatures. This estimated effect, however, is not statistically significant. A similar mitigating effect has been found by Wang et al. (2021) with field trial data from Wisconsin. What stands out are the interaction effects between GE adoption and VPD variables, both of which are negative, large, and statistically significant. Whereas the growing-season VPD has a positive coefficient absent GE, the net effect is negative after the full GE adoption. These findings appear consistent with a strand of literature documenting an increased yield vulnerability to water stress after the introduction of GE varieties (e.g., Lobell et al., 2014). GE-precipitation interactions, on the other hand, seem to reduce yield sensitivity to higher rainfalls in the growing season.

Because Model 2 captures the effects of GE traits and weather variables in a more nuanced fashion, and the inclusion of interaction effects is supported by the F test, in what follows we rely on this model to analyze the impact of climate change on yields.

5 | YIELD PROJECTIONS WITH CLIMATE CHANGE

Using the estimated yield models, we can assess the extent to which technology improvements, and climate change, are likely to affect future yields. For this purpose, future weather variables are used to forecast maize yields under alternative growth regimes and climate change scenarios. If we denote future variables by the superscript "f", and the estimated parameters of the model in Equation (1) by a hat, the projections for future yields are expressed as:

$$\hat{y}_{it}^{f} = \hat{\alpha}_i + \mathbf{X}_{it}^{f}\left(\hat{\boldsymbol{\beta}} + \hat{\boldsymbol{\delta}}\, G_s^0\right) + \hat{\gamma}\, G_s^0 + \hat{\tau}_s T_t \quad (\text{forecast with projected future weather}), \tag{2}$$

$$\tilde{y}_{it}^{f} = \hat{\alpha}_i + \mathbf{X}_{i}^{h}\left(\hat{\boldsymbol{\beta}} + \hat{\boldsymbol{\delta}}\, G_s^0\right) + \hat{\gamma}\, G_s^0 + \hat{\tau}_s T_t \quad (\text{forecast with model-implied historical weather}), \tag{3}$$

where $t \in \{2040, \ldots, 2059\}$ for mid-century projections and $t \in \{2080, \ldots, 2099\}$ for end-of-century projections. In Equation (3), $\mathbf{X}_i^h$ denotes the (row) vector of weather variables under the presumption of a stationary climate, proxied by their average value of weather variables predicted by the relevant climate model over the historical period 1981–2005. By contrast, $\mathbf{X}_{it}^f$ in Equation (2) denotes the (row) vector of projected future weather variables according to the relevant climate change model and warming scenario. Note that, in all future periods, the adoption rates of GE varieties are held constant at G_s^0. Specifically, we fix this rate at the observed 2020 level.[4]

Although this may be obvious, we emphasize that the counterfactual projections based on Equations (2) and (3) are not meant to be unconditional forecasts—among other things, we do not attempt at forecasting what future agronomic technologies might be. Rather, these projections are conditional forecasts about how anticipated future climatic conditions are likely to affect realized maize yields given the estimated response to weather variables over the historical period, and also the continuation of crop improvement as captured by the underlying trend.

Predicted counterfactual yields under a specific climate change scenario (using Equation [2]) and under a stationary climate scenario (using Equation [3]) are obtained at the county level. These predictions are then aggregated to the national level using county-level weights based on the acreage of harvested maize in the 2017 Census of Agriculture.

The "yield gap" due to climate change is defined here as the difference between the expected yield with the anticipated climate change and the yield one would expect given stationary climate conditions (at recent historical levels)—in both cases, conditional on normal technological progress

[4]The national average for this adoption rate is about 91%. We view this as a somewhat more conservative assumption than the alternative of full adoption (i.e., $G_s^0 = 1, \forall\, s$).

as captured by the underlying trend. Estimates of such yield shortfalls are reported in Table 2. It is apparent that climate change is predicted to have sizeable impacts on maize yield. Across all 20 GCMs, the ensemble mean at mid-century indicates a yield shortfall of 25.5 bu./acre for the RCP 4.5 scenario, and 37 bu./acre for the RPC 8.5 scenario. The estimated yield gaps are larger at the end-century, with an average shortfall due to climate change of 34.7 bu./acre for RCP 4.5 and 82.4 bu./acre for RCP 8.5. It is also apparent that the various GCMs lead to considerable variability in predicted outcomes. For mid-century, predicted yield shortfalls range from a minimum of 3.8 bu./acre (model MRI-CGCM3 under RCP 4.5) to a maximum of 69.9 bu./acre (model MIROC-ESM-CHEM under RCP 8.5). Similarly, at the end century, predicted yield shortfalls range from a minimum of 7.3 bu./acre (again with model MRI-CGCM3 under RCP 4.5) to a maximum of 146.8 bu./acre (model HadGEM2-CC365 under RCP 8.5).

TABLE 2 Maize yield shortfalls due to anticipated climate change: 20 climate models

	Mid century		End of century	
Global climate model	**RCP 4.5**	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
HadGEM2-ES365	44.0	64.6	67.1	129.5
HadGEM2-CC365	37.7	68.7	44.8	146.8
MIROC-ESM	34.9	66.7	52.2	133.8
MIROC-ESM-CHEM	43.5	69.9	49.6	121
NorESM1-M	38.1	49.7	52.3	110.6
CCSM4	32.2	52.4	46.6	91.7
bcc-csm1-1-m	28.7	38.8	40.8	91.1
MIROC5	35.0	45.8	26.5	79.6
BNU-ESM	28.3	40.5	33.8	83.3
CSIRO-Mk3-6-0	25.9	35.5	36.2	80.4
bcc-csm1-1	31.5	29.7	28.4	84.7
IPSL-CM5A-MR	23.5	22.7	35.7	83.5
CanESM2	19.3	19.8	31.4	78.9
IPSL-CM5A-LR	19.0	23.3	31.5	64.7
GFDL-ESM2G	15.5	23.8	23.8	53
CNRM-CM5	11.8	25	25.4	50.6
inmcm4	15.7	18	27	47.3
GFDL-ESM2M	13.9	18.5	21.4	43
IPSL-CM5B-LR	7.4	18.2	12	50.5
MRI-CGCM3	3.8	8.2	7.3	23.9
Mean	25.5	37	34.7	82.4
Min	3.8	8.2	7.3	23.9
Max	44	69.9	67.1	146.8

Note: Models are listed in descending order based on the overall impact (average over mid-century and end-of-century, and over both RCP 4.5 and RCP 8.5).

Also worth noting, climate forecasts from HadGEM2-ES and NorESM1-M, perhaps the two most widely used to contrast the impact of future climate predictions on agricultural productivity (e.g., X. Chen & Chen, 2018; Malikov et al., 2020; Ortiz-Bobea, 2020; Warszawski et al., 2014), turn out to be quite pessimistic and not representative of the ensemble means of the full set of GCMs. In particular, HadGEM2-ES is the model that predicts the worst outcomes for future maize yields.

To appreciate the magnitude of the estimated yield shortfalls, we can use the estimated yield gains realized by the adoption of first-generation GE varieties as of 2020 as a benchmark. The yield gain due to the (nearly complete) adoption of GE varieties, as implied by our estimated model, is 13.01 bu./acre. Thus, the estimated yield gaps due to climate change at mid-century range from approximately 2.0 to 2.7 times the entire realized yield gains made possible by the development and widespread adoption of GE varieties. By the end of the century, the estimated yield gaps range from 2.8 times to 6.3 times the GE yield gain.

The results discussed in the forgoing are illustrated in Figure 1 (panel A pertains to the RCP 4.5 pathway, and panel B is for RCP 8.5). The effects of anticipated climate change on

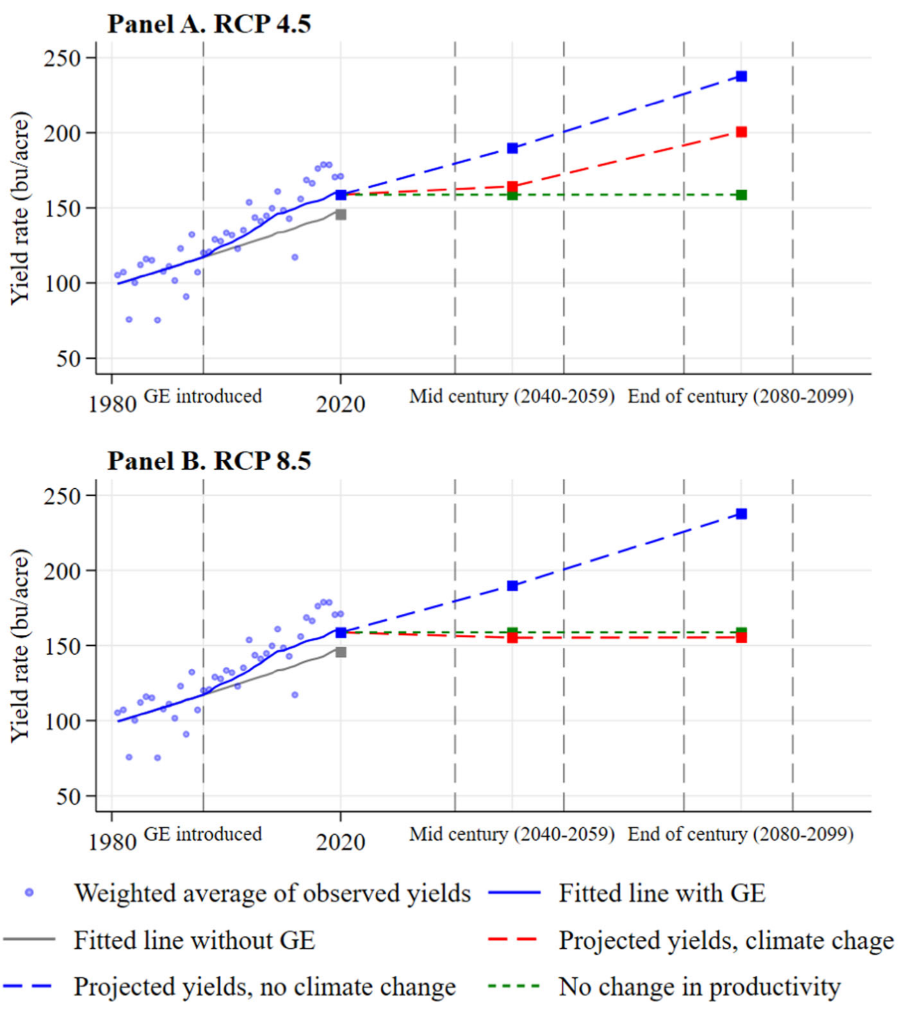

FIGURE 1 Forecasted yields under climate change, ensemble mean of 20 GCMs. GE, genetically engineered; GCM, global climate model.

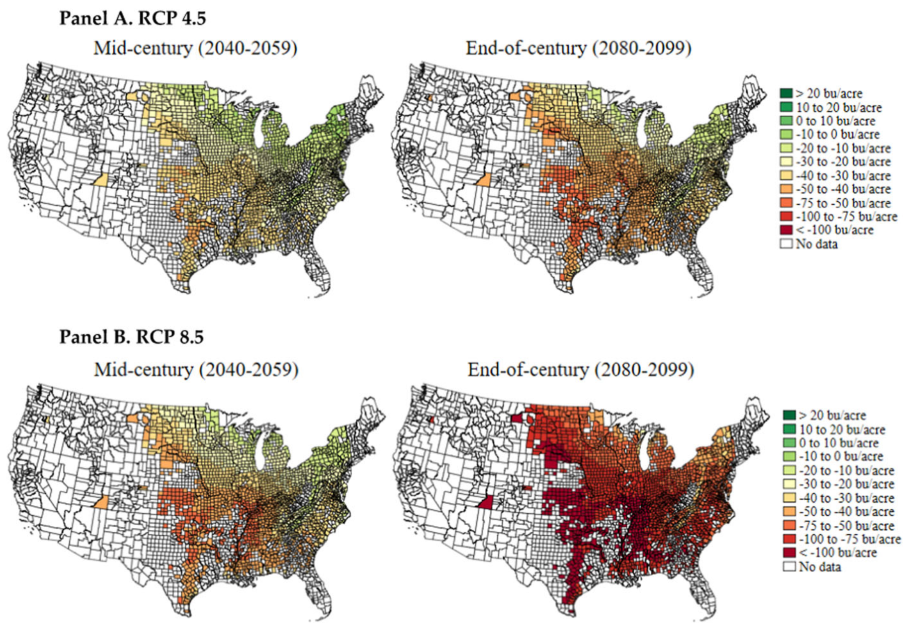

FIGURE 2 County-wise yield gap under climate change, the ensemble mean of 20 GCMs Panel A. RCP 4.5 Panel B. RCP 8.5. GCM, global climate model.

maize yields are quite dramatic. For the more pessimistic RCP 8.5 pathway, climate change totally offsets the yield gains from the underlying technical progress (as captured by the trend in the estimated model), such that mid-century and end-century projected yields are actually lower than 2020 yields.

Figure 2 describes the spatial distribution of estimated yield gaps, depending on the period and scenario of reference. It is apparent that there exists considerable spatial variation in the yield gaps attributable to climate change. Counties in the southern region turn out to be more sensitive and vulnerable to warming climate change compared to the northern regions. This result is consistent with the observation that southern counties are more likely to be exposed to climatic conditions exceeding a critical threshold (e.g., Schlenker and Roberts [2009] report 29°C as a crucial threshold for maize growth).

Burke et al. (2015) emphasize the importance of considering the role of climate uncertainty when making inferences about economic outcomes of interest. Our analysis is well positioned to gauge the impact of climate uncertainty, as we have relied on a broad set of 20 GCMs available to us in MACA. Results are reported in Figure 3, which shows the range of climate impacts by the type of uncertainty for the two warming scenarios considered, RCP 4.5 (panel A) and RCP 8.5 (panel B). These diagrams illustrate the fact that the uncertainty of our estimates arises mostly from climate uncertainty, whereas the role of regression uncertainty is minimal.

Lee et al. (2022) provide more details on various aspects of the model, and investigate the robustness of the results discussed in the foregoing with respect to using the semi-log parameterization for yields, or using a more restrictive geographic sample. They also present a decomposition of estimated future yield shortfalls according to projected heat and water stress determinants, although they note that meaningful separation of heat and water stress in the model is inherently problematic.

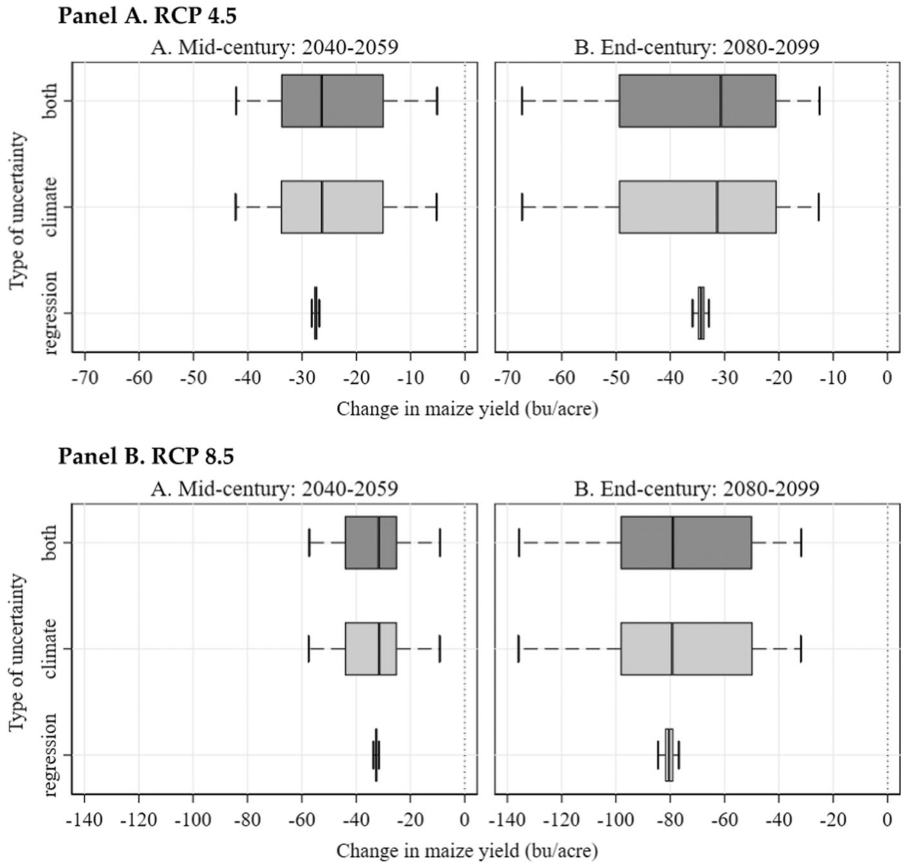

FIGURE 3 Uncertainty range from all 20 climate models Panel A. RCP 4.5 Panel B. RCP 8.5. For each type of uncertainty, the box shows the upper quartile and the lower quartile across bootstrap replications for yield gaps and the middle line indicates the median of the estimated yield gaps. Whiskers range from the 5th percentile to the 95th percentile of the bootstrap replications.

6 | CONCLUSION

Agriculture is at the forefront of anticipated impacts of climate change, and considerable evidence has accumulated to suggest that, without countervailing actions, large negative consequences are probable. Whereas a number of strategies might be helpful to blunt climate change's impacts on the food supply, there is a growing sense that major adaptation efforts will be necessary. Successful adaptation may require purposeful, directed investments in R&D to develop suitable new technologies. Just how large is the innovation effort required for successful adaptation in agriculture? To shed some light on this question, in this paper we focus on maize production in the United States. Maize is the most important field crop in the country and one that has benefited greatly from major technological advances over the last few decades, including the development and widespread adoption of GE varieties. The latter constitutes the most prominent set of agricultural innovations since the green revolution. As the nature and scale of this GE revolution are well understood, in this paper we propose to use it as a yardstick—that is, to gauge the scope of the innovation task required for adaptation, to offset the impacts of anticipated climate change, in terms of multiples of what was achieved by the widespread adoption of first-generation GE traits in maize.

To be clear, our focus on first-generation GE traits is not meant to suggest that GE technologies have no further role to play going forward. Our point is that the GE productivity gains captured by our yield model relate to a clearly defined set of innovations—first-generation GE varieties embedding agronomic traits—that were rapidly diffused (essentially to full adoption) over a relatively short time period. They are best viewed as a one-time bump in yields and, as such, provide an attractive yardstick to measure the extent of the innovation challenges posed by adaptation to climate change. Going forward, genetic engineering is expected to continue to play a key role in crop improvement. Indeed, promising new GE technologies such as CRISPR, which offer novel methods to control and improve crops' genomes, are only beginning to be deployed (K. Chen et al., 2019). For these new generations of GE technologies to affect yields in the face of changing climatic conditions, however, targeted new R&D investments will be needed —over and above those required to sustain the underlying trend of yield improvement estimated over the sample period (which we maintain in all counterfactuals).

We confirm the finding of previous studies that GE traits have contributed significantly to increasing maize yields. The estimated parameters suggest that the full adoption of (first-generation) GE traits leads to yield improvement in the range of 14.2 to 16.6 bushels per acre. Next, we use the model to forecast the yield impact, at both mid-century and end-of-the-century, of weather patterns projected from a broad set of 20 climate models under two warming scenarios (RCP 4.5 and RCP 8.5). We find that the average yield shortfalls arising from adverse climate developments are large. The ensemble means across 20 GCMs indicate that climate change is expected to decrease maize yields in the range of 25.5–37 bu./acre at mid-century, and in the range of 34.7–82.4 by the end century. These yield shortfalls correspond to a range of 2.0–2.7 times the yield gain from GE over the observed historical period at mid-century, and to a range of 2.8–6.3 times the GE yield gain at the end-century. Finally, we establish that little uncertainty originates from the estimated yield regression model and that virtually all of the estimated variability of predicted yield impacts of climate change is due to climate uncertainty.

Extrapolation of the estimated maize yield shortfalls due to climate change to general agricultural productivity is subject to some caveats, of course. In particular, when aggregating county-level results, including the counterfactuals under climate change conditions, we have relied on fixed county-specific weights. Thus, our results do not account for a margin of adjustment that has been recognized as very relevant in this context—the possibility that climate change may affect comparative advantage enough that the kind of crops grown, and their intensities, may spatially relocate (Costinot et al., 2016). Crop switching, when feasible, can of course reduce the overall impact of climate change on agricultural productivity (Rising & Devineni, 2020).

Notwithstanding the foregoing qualifications, the results we have presented imply that the scope of adaptation to climate change, vis-à-vis agricultural productivity, is very challenging. For the case of US maize, severe yield shortfalls are to be expected by the end of the century under a wide range of climate model projections, especially for the warming scenario RCP 8.5. We find that the estimated yield shortfalls are several times larger than the entire productivity gains due to the adoption of first-generation GE traits. This is particularly significant given that the development and diffusion of such GE traits were made possible by a unique confluence of propitious circumstances —by leveraging breakthrough advances in recombinant DNA techniques, unprecedented research efforts by agrochemical and seed companies led to the invention of insect-resistant and herbicide-tolerant traits that, once introduced into elite germplasm, were rapidly adopted by farmers. The underlying R&D investments were substantial—for example, private sector expenditure on crop seed and biotechnology R&D is estimated to have increased eightfold, in real terms, between 1994 and 2010 (Heisey & Fuglie, 2011). In this paper, we find that the magnitude of the impacts of the (first generation) GE revolution on crop improvement may need to be replicated several times to offset the damaging impact of climate change on maize yield. Large, sustained, and targeted research efforts are needed to counter the negative implications of anticipated climate change.

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DATA AVAILABILITY STATEMENT

Data used are fully described in the main text and the supplementary appendix.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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