

LETTER • OPEN ACCESS

Is another genetic revolution needed to offset climate change impacts for US maize yields?

To cite this article: Ariel Ortiz-Bobea and Jesse Tack 2018 *Environ. Res. Lett.* **13** 124009

View the [article online](#) for updates and enhancements.

You may also like

- [Foreign yield shocks and domestic price variability: the case of maize in developing countries](#)
Bowen Chen and Nelson B Villoria
- [Optimizing sowing window and cultivar choice can boost China's maize yield under 1.5 °C and 2 °C global warming](#)
Mingxia Huang, Jing Wang, Bin Wang et al.
- [Mid-20th century warming hole boosts US maize yields](#)
Trevor F Partridge, Jonathan M Winter, Lin Liu et al.

Breath Biopsy Conference

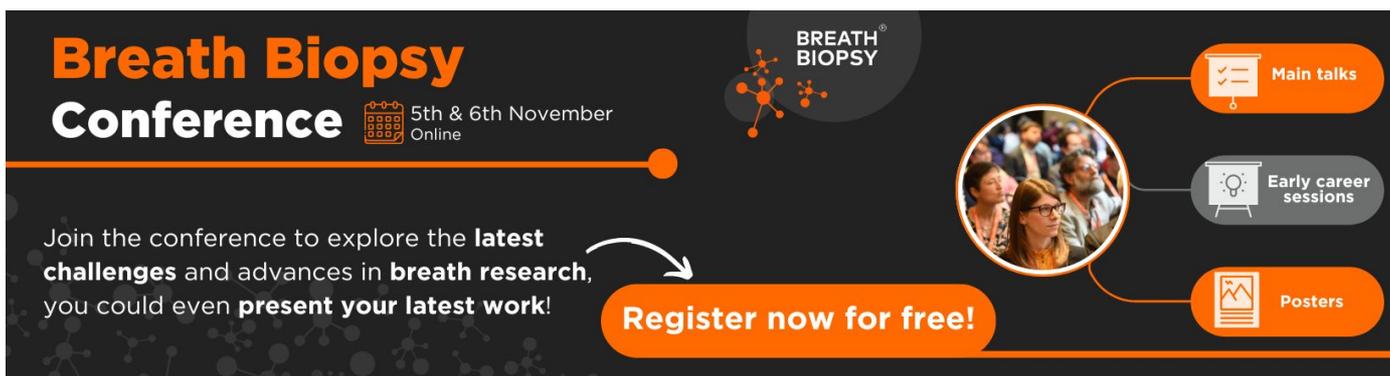
5th & 6th November Online

Join the conference to explore the **latest challenges** and advances in **breath research**, you could even **present your latest work!**

Register now for free!

BREATH BIOPSY

- Main talks
- Early career sessions
- Posters



Environmental Research Letters



LETTER

Is another genetic revolution needed to offset climate change impacts for US maize yields?

OPEN ACCESS

RECEIVED
9 May 2018REVISED
4 October 2018ACCEPTED FOR PUBLICATION
19 October 2018PUBLISHED
29 November 2018

Original content from this work may be used under the terms of the [Creative Commons Attribution 3.0 licence](#).

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

Ariel Ortiz-Bobea¹ and Jesse Tack² ¹ Charles H. Dyson School of Applied Economics and Management, Cornell University, Ithaca, NY 14853, United States of America² Department of Agricultural Economics, Kansas State University, Manhattan, KS 66506, United States of AmericaE-mail: ao332@cornell.edu**Keywords:** agriculture, climate change, global warming, genetic engineering, GMO, corn, maizeSupplementary material for this article is available [online](#)**Abstract**

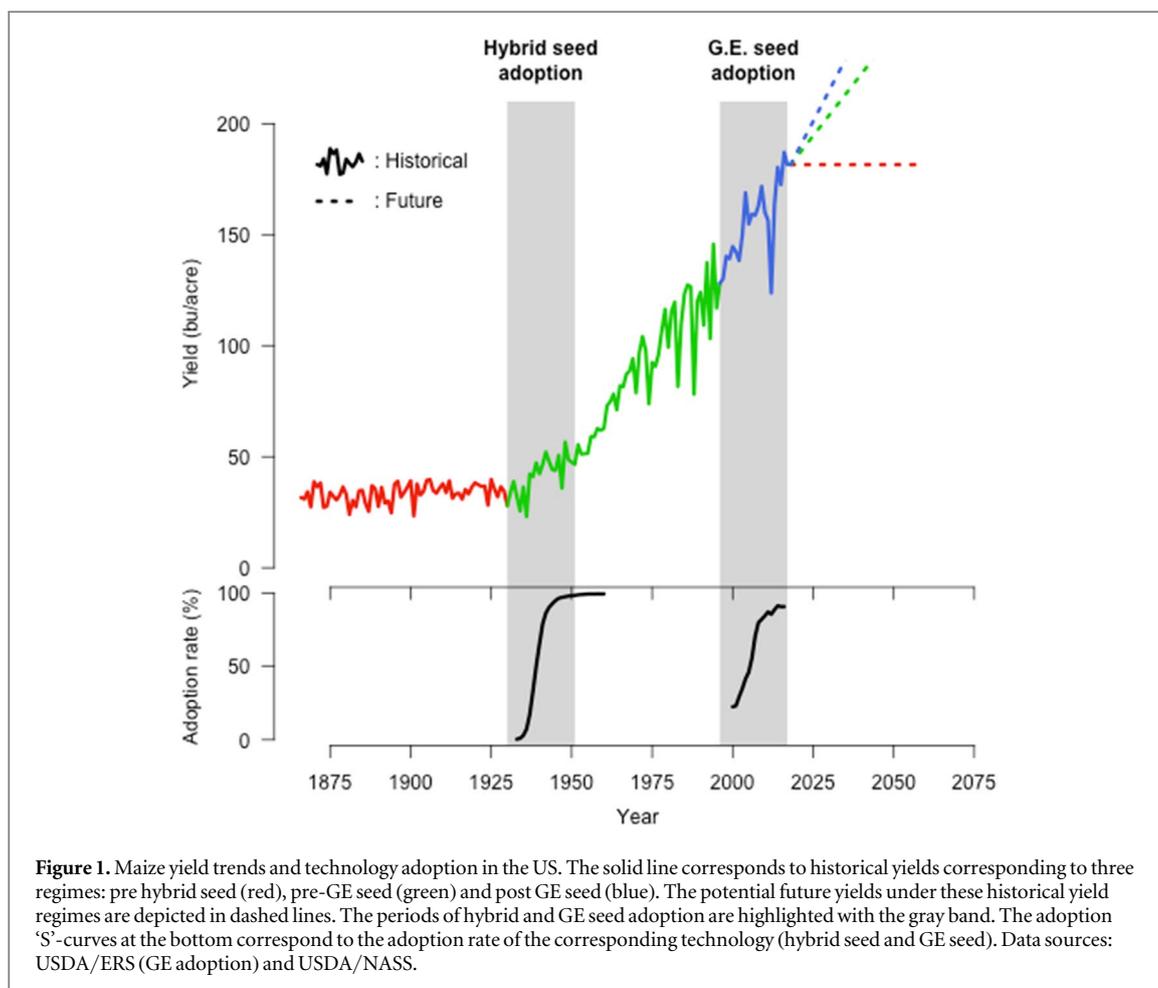
Predictions of future food supply under climate change rely on projected crop yield trends, which are typically based upon retrospective empirical analyses of historical yield gains. However, the estimation of these trends is difficult given the evolving impact of agricultural technologies and confounding influences such as weather. Here, we evaluate the effect of climate change on United States (US) maize yields in light of the productivity gains associated with the period of rapid adoption of genetically engineered (GE) seeds. We find that yield gains on the order of those experienced during the adoption of GE maize are needed to offset climate change impacts under the business-as-usual scenario, and that smaller gains, such as those associated with the pre-GE era in the 1980s and early 90s, would likely imply yield reductions below current levels. Although this study cannot identify the biophysical drivers of past and future maize yields, it helps contextualize the yield growth requirements necessary to counterbalance projected yield losses under climate change. Outside of the US, our findings have important implications for regions lagging in the adoption of new technologies which could help offset the detrimental effects of climate change.

1. Introduction

A major challenge for global food security is ensuring that technological progress will be sufficient to compensate for the effects of a warmer climate and rising food demand (Lobell and Asner 2003, Lobell and Field 2007, Schmidhuber and Tubiello 2007, Lobell *et al* 2011, Butler and Huybers 2013, Lobell *et al* 2013, Ray *et al* 2013, Wheeler and Von Braun 2013, Burke and Emerick 2016). Without substantial gains in productivity, the rising global demand for food could lead to higher food prices thereby incentivizing conversion of rainforests, wetlands, and grasslands to farmland (Alston *et al* 2009, Duvick and Cassman 1999). There has been much work estimating the potential impact of climate change on maize yields using historical data coupled with statistical models (Lobell and Asner 2003, Schlenker and Roberts 2009, Lobell *et al* 2011, Butler and Huybers 2013, Burke and Emerick 2016, Gammans *et al* 2017), and recent research suggests that these

statistical-based approaches provide similar estimates to process-based models (Roberts *et al* 2017). A key empirical challenge for statistical models is unpacking the effect of weather on crop yields from that of technological differences across both locations and time. The conventional approach to address this issue is to introduce time trends in the statistical model to ‘control for’ ongoing technological advancement. In general, the focus is not on correctly specifying the pace of technological change *per se*, but rather on evaluating whether climate change impact projections remain insensitive to alternative assumptions about the time trend.

Nonetheless, there is growing interest in improving the estimation of technological trends with the goal of analyzing emerging food security concerns for a growing global population (Dyson 1999, Evenson 1999, Hafner 2003, Fisher *et al* 2010, Jaggard *et al* 2010, Cassman *et al* 2011, Ray *et al* 2012, 2013, Grassini *et al* 2013, Tollenaar *et al* 2017). Studies



typically explore alternative trend specifications, but do not account for both structural changes of the growth rate and the confounding influence of weather. The presence of regime shifts or ‘breaks’ in historical data, which we verify empirically in this study, is important for considering plausible future trends as it is difficult—if not impossible—to forecast structural changes *ex ante*. How we characterize historical changes in technology has crucial implications for climate change and food security projections as they require assumptions on the future pace of yield progress (Dyson 1999, Evenson 1999, Jaggard *et al* 2010, Cassman *et al* 2011, Ray *et al* 2013).

The widespread adoption of genetically engineered (GE) varieties in United States (US) maize production starting in 1996 was a major technological revolution (Shi *et al* 2013, Xu *et al* 2013, Lusk *et al* 2017). GE varieties are associated with higher yields typically attributed to the inclusion of genes transmitted by the *Bacillus thuringiensis* bacterium that make plant tissues toxic to pests (Nolan and Santos 2012, Xu *et al* 2013, Barrows *et al* 2014, Chavas *et al* 2014, Klümper and Qaim 2014, Lusk *et al* 2017). Figure 1 provides a broad perspective on maize yield since the late 1800s and highlights the existence of several technological regimes that have occurred following the introduction of hybrids in the 1920s and GE varieties in the 1990s.

While yields stagnated for many decades until the adoption of hybrid seeds in 1930s, yield increases have been substantial particularly since the adoption of GE seed technologies. However, it remains unclear today which of these yield growth regime(s) best represents plausible scenarios of future progress given the potential biophysical limits on crop growth (Duvick and Cassman 1999, Lobell *et al* 2009). These technological regimes are useful reference points for exploring future yield trends in a warming world.

Our research seeks to inform the technological needs under climate change. More specifically, we aim to distinguish US maize yield trends in the pre- and post-GE era, and contrast these to predicted yield impacts based on climate change models. While the yield differences between these two eras cannot be solely attributed to the adoption of GE seeds, this comparison sheds light generally on the necessary technological advancements required to offset climate change impacts. Here, we provide a novel approach for large-scale estimation of spatially heterogeneous technological effects and climate change impacts simultaneously within a unified econometric model. Importantly, this approach does not require data on actual GE adoption rates, which is typically unavailable or measured at an aggregate level in observational settings, but rather only requires knowledge of when

GE varieties became available. Analysis of county-level yields spanning 1981–2015 show that annual yield gains of a similar magnitude as those experienced during the adoption of GE maize are needed to offset climate change impacts under the business-as-usual scenario, and that smaller gains such as those associated with the pre-GE era in the 1980s and early 90s would likely imply yield reductions below current levels. In addition, we show that accurate estimation of historical yield trends requires (i) allowing for a structural break when GE varieties are initially introduced and (ii) controlling for the confounding influence of weather.

The raw data in this study include annual county-level maize yields, monthly precipitation, and daily minimum and maximum temperature observations. We focus on 8 states constituting the US Corn Belt in which GE maize has reached near-complete adoption. The data contain 17 000 observations spanning 500 counties during 1981–2014. As a departure from previous work, we model trends using a piece-wise linear spline with an inflection point in 1996 to allow the trend to vary across the pre-GE (1981–1995) and post-GE (1996–2014) periods. Recent work suggests that yield gains from GE seed adoption have been spatially heterogeneous (Lusk *et al* 2017), so we rely on hierarchical mixed models with trends varying across agricultural reporting districts within each state. Crop reporting districts are USDA administrative units within each state that contain groupings of counties.

2. Methods

2.1. Data sources

We rely on county-level maize yield data from USDA/NASS (1981–2014). We also rely on average acreage over the sample period as weights for computing aggregate regional impacts. The analysis is based on a balanced panel of 500 counties in eight Midwestern states (Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio, and Wisconsin). Maize production in these counties is mostly rain-fed.

For weather data we rely on monthly precipitation and daily maximum, minimum, and average temperature from the PRISM Climate Group (<http://www.prism.oregonstate.edu>). The PRISM data is a gridded climate dataset with a 4 km spatial resolution that is the official climatological data of the USDA and has been widely used in the climate impacts literature (e.g. Schlenker and Roberts, 2009). The daily PRISM data is available since 1981 and we rely on the 1981–2014 period for our analysis. Daily temperatures are processed into temperature exposure bins of 1 °C each, from –15 °C to 50 °C, which are necessary to estimate non-linear effects of temperature following Schlenker and Roberts (2009). The temperature exposure data is computed based on a double sine curve passing

through the minimum and maximum of each consecutive day at each grid.

Because the analysis is conducted at the county-level, we aggregate the gridded data up to the county level to match the agricultural production data based on the amount of cropland contained in each PRISM grid, which we derive from USDA's 30 m resolution Crop Data Layer.

2.2. Regression models

We specify the statistical model using a linear multi-level model:

$$y_{it} = \sum_{k=1}^d \gamma_k \underbrace{\sum_{h=\underline{h}}^{\bar{h}} T_k(h) [\Phi_{it}(h+1) - \Phi_{it}(h)]}_{z_{it,k}} + \beta_1 p_{it} + \beta_2 p_{it}^2 + v_{it} + \varepsilon_{it},$$

where y_{it} is the natural log of maize yield in county i and year t . The fixed effects portion (in the multilevel model parlance) of the model includes the effects of temperature exposure $\sum_{k=1}^d \gamma_k z_{it,k}$ and the effects of precipitation $\beta_1 p_{it} + \beta_2 p_{it}^2$. The random effects captured by v_{it} include random intercepts across counties and random piecewise linear trends across districts:

$$v_{it} = u_{0i} + u_{1g}t + u_{2g}(t - 16),$$

where t denotes the trend variable with value 16 in the year 1996 and the subscript g denotes ag districts. Parameter estimates are obtained using the lmer function in R and reported in table S1 (available online: stacks.iop.org/ERL/13/124009/mmedia).

All weather variables are aggregated over the April–September growing season following modeling choices in the literature. Our approach is similar to Schlenker and Roberts (2009) in that it allows for non-linear effects of temperature exposure over the season. More specifically, $\Phi_{it}(h+1) - \Phi_{it}(h)$ is the exposure to temperature bin h over the season, and $T_k(h)$ is the element in column k and row h of the basis matrix of a Chebyshev polynomial of degree d defined over temperature bins $(\underline{h}, \dots, \bar{h})$. Unless otherwise noted, all models in the study rely on an 8th degree polynomial with $\underline{h} = 0$ and $\bar{h} = 36$ °C so that there is enough exposure at the extreme bins. In a sense, the variable $z_{it,k}$ is a locally-weighted transformation of temperature bins, which assumes a smooth response to exposure to different temperature levels. We also considered polynomial specifications of various degrees and find the results to be fairly insensitive to the functional form. The effects of precipitation are captured by the inclusion of linear and quadratic terms for seasonal precipitation.

Table S1 shows that the multilevel model produces similar results to the more commonly used panel data 'fixed effects' models used in the literature. The estimated yield-temperature response curve for the multilevel model is similar to those from previous studies (figure S1). We prefer the multilevel model here as it allows for a parsimonious expansion of the trend

effects to be heterogeneous across districts, which permits a more localized representation of cross-sectional trend differences compared to previous studies that allow trends to vary at the state-level. This is an important consideration given previous evidence of localized differences in GE adoption effects (Lusk *et al* 2017).

To represent the variability of estimated effects and projections we rely on a block-bootstrap procedure whereby we estimate the above model 1000 times with data resampled with replacement by year. This follows the bootstrap aggregating or ‘bagging’ procedure developed commonly used in machine learning (Breiman 1996).

2.3. Climate projections and impacts

The calculation of climate change impacts largely follows the recommendations laid out in Auffhammer *et al* (2013). Future projections of changes in temperature and precipitation are derived from models archived as part of the Climate Model Intercomparison Project Phase 5 (CMIP5) project, and include the same collection of General Circulation Model (GCM) simulations used for the 5th Intergovernmental Panel on Climate Change (IPCC). Native GCM spatial resolution tends to be between 50–200 km, which is much coarser than required for our estimates of crop yields. The native GCM data is therefore downscaled based on the approach proposed by Mosier *et al* (2014).

The fine resolution target is the 4 km PRISM grid. The coarse resolution GCM data originate from the IPCC models with surface air temperature (tas), and precipitation (pr) fields available at monthly timescales, and for both historical and climate change scenarios. This list of models is restricted to the following subset of all CMIP5 GCMs: CNRM-CM5, FGOALS-g2, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, HadGEM2-CC, HadGEM2-ES, INM-CM4, IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC5, MIROC-ESM-CHEM, MIROC-ESM, MRI-CGCM3, and MRI-ESM1. Several models include multiple ensemble members, and all include simulations of different representative concentration pathways (RCPs). Here, we use the RCP 2.6, 4.5, 6.0 and 8.5 scenarios, which represent total net increase in longwave radiative forcing of 2.6, 4.5, 6.0 and 8.5 W m⁻² by the end of the 21st Century, respectively.

Our initial step is to compute historical ‘reference’ climatologies for each variable at weekly and monthly timescales from each CMIP5 model at its native resolution using the period (of the model) from 1950–2000. Likewise, we compute future climatologies from each GCM for the periods between 2025–2075 and 2050–2100 for each RCP and ensemble. Next, we computed changes in model mean ($\Delta\mu$) according to $\Delta\mu = \mu_{future} - \mu_{historical}$ for temperature (tas), and $\Delta\mu = (\mu_{future} - \mu_{historical}) / \mu_{historical}$ for precipitation (pr). The changes in temperature are

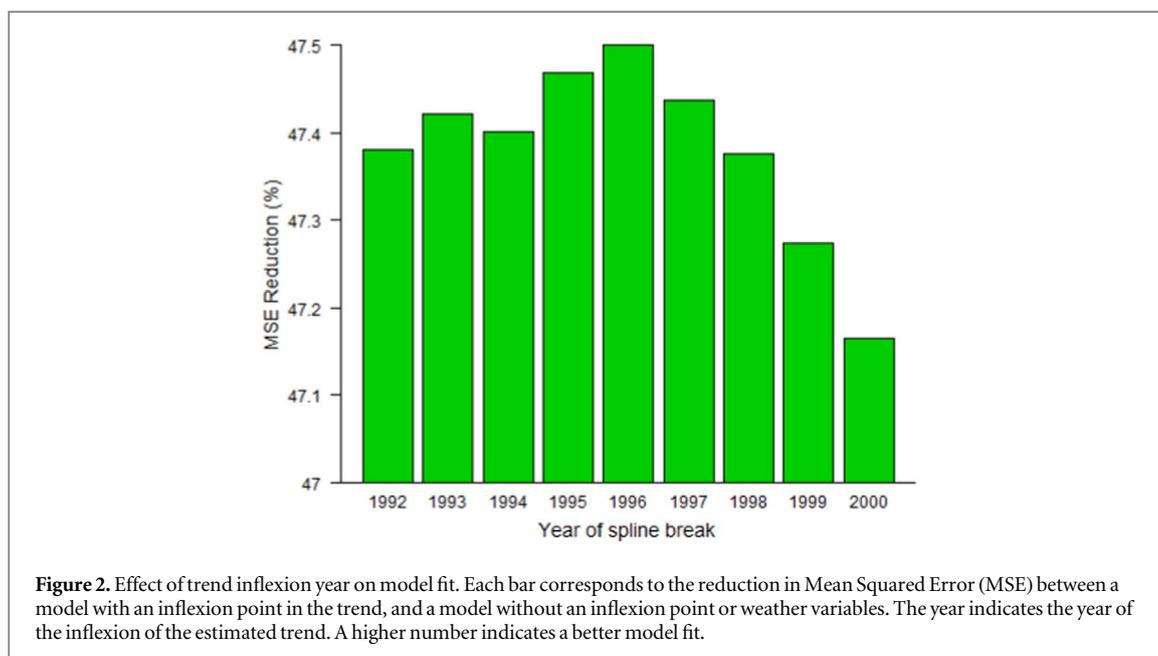
therefore to be regarded as actual differences in the mean and variance of the quantity itself, whereas the changes in precipitation are fractional increases or decreases relative to historical climatology. Changes in mean climatology are computed from each model at each grid point for all ensemble members and scenarios at model resolution prior to interpolation. The final two steps in the downscaling procedure are to (i) interpolate the modified climatologies of the future to the target (4 km) grid, and then (ii) apply those changes to PRISM climatology.

Following the conventional practices in the literature, we calculate county-level climate change impacts on yields in percentage terms as $impact_i = 100(\exp [(z_{1i} - z_{0i})\gamma + (p_{1i} - p_{0i})\beta] - 1)$ where (z_{0i} , p_{0i}) are the baseline temperature and precipitation climate measures and (z_{1i} , p_{1i}) are the measures under climate change for each county i . The aggregated impacts for the entire region are the acreage-weighted summation of the county-level impacts.

3. Results

Accounting for weather realizations may be critical for estimating yield trends correctly. Intuitively, a string of peculiar weather realizations could bias the estimation of the trends if such conditions are unaccounted for and materialize disproportionately in either the pre- or the post-GE period. We therefore compare trend estimates using a single linear trend versus a piecewise linear trend with an inflection point at 1996. We also consider random effects for these trends at both the agricultural district and county levels, as well as the inclusion of weather variables as controls. Our preferred model included a piecewise linear trend with random trends at the district level and weather variables included as controls, as it exhibited the lowest AIC (calculated using the approach of Greven and Kneib (2010) for random effects models with the R package ‘caIC4’) and similar out-of-sample forecasting accuracy among the alternatives (table S2). We also found that the placement of the knot at 1996 is optimal (figure 2).

We find maize yield trends increased by almost 70 percent around the period of rapid adoption of GE seeds. We could identify this finding only by accounting for the confounding influence of weather. More precisely, the first two models suggest GE seed adoption did not alter the yield growth trajectory. However, the third model—which predicts yields most accurately—points to large differences in the trend estimates between the pre- and post-GE periods. The trend estimates for the three models are illustrated for the state of Iowa in figure 3 and mirror similar results for other states (figures S2–S8). This finding is consistent with previous work demonstrating the importance of controlling for weather realizations when estimating yield gains from GE adoption (Lusk



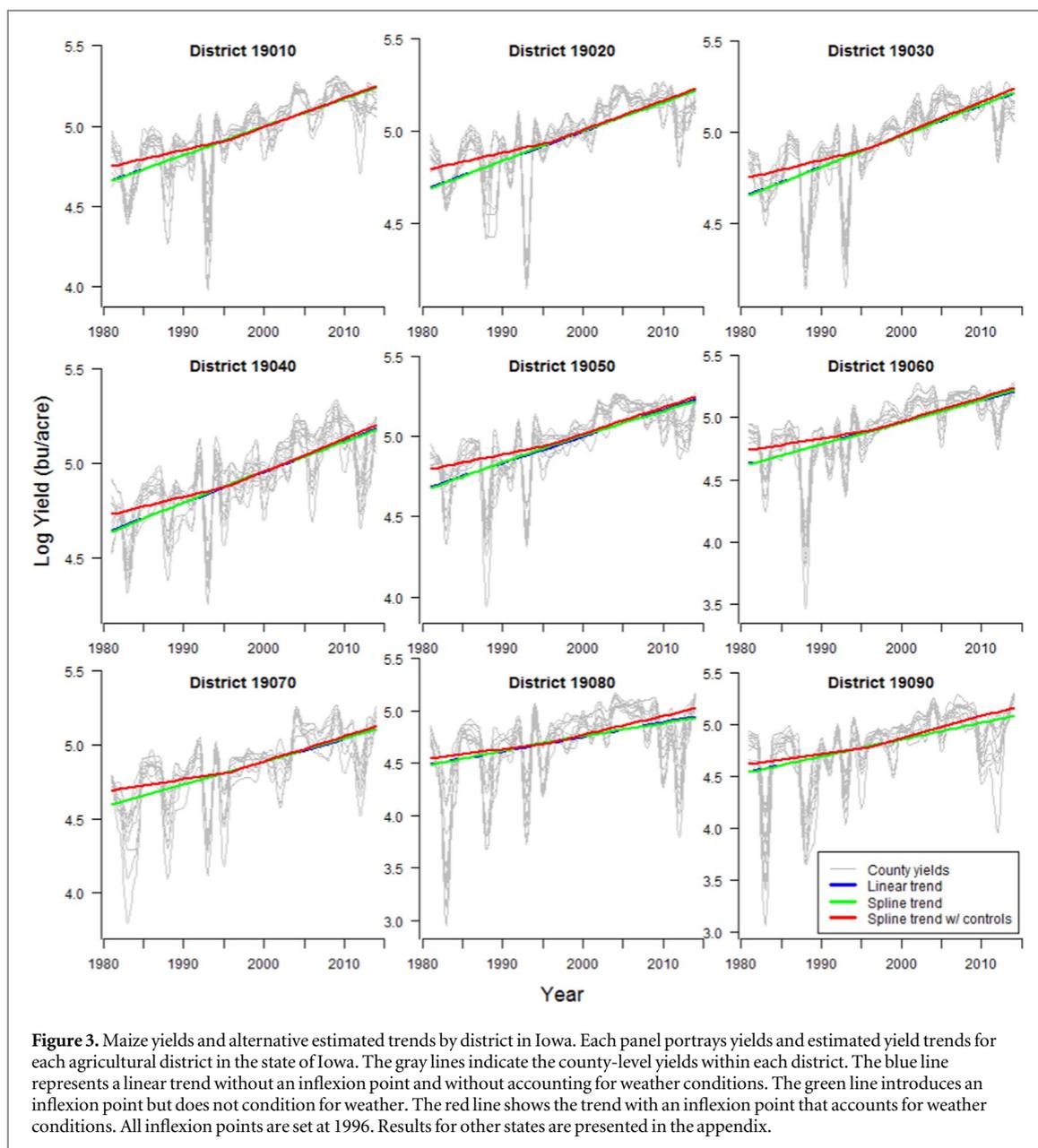
et al 2017). Since log-yield is the dependent variable in our regression model, the slopes of the piecewise linear trend segments provide an estimate of the annual percentage-change in yields. On average across counties, maize yields grew by 0.94 and 1.59% yr^{-1} in each of the two periods, indicating GE seed adoption is associated with a net annual yield growth increase of 0.65% points. Given a baseline yield of 120 bushels/acre—approximately the five-year sample-average in these states prior to GE adoption—the compounded gain associated with this technological transition over a 22 year period spanning 1996 to the present is approximately 17.5 bushels per acre. Even though we cannot solely attribute the yield gains to GE seeds alone within our framework, our estimate is strikingly similar in magnitude to estimates based on side-by-side comparisons of GE versus non-GE hybrids in field trials that include cultivar-specific yield observations alongside an extensive set of agronomic and climatic controls (Nolan and Santos, 2012).

The trend estimates exhibit extensive cross-sectional heterogeneity. Across counties, the pre-GE trends span 0.64%–1.34% whereas post-GE trends range from 1.07% to 2.15% with pre-post differences ranging between 0.29% and 1.04% points (figures S9–S11). This heterogeneity indicates that technological change has impacted different regions very differently. That is, while new technologies such as GE seeds are widely adopted, benefits can vary substantially across alternative growing conditions associated with local biotic and abiotic factors and interactions thereof.

The effect of climate change on crop yields will severely undercut potential gains from technological progress based on a widely-used GCM. We compare trend estimates with the gross impact of climate change on yields. To ensure comparability we

annualize climate change impacts by taking the point-prediction at a given future date divided by the number of years until that date. For example, the total estimated impact is a 77% yield reduction on average across counties for 2050–2100 under the HadGEM2-ES GCM and the business-as-usual RCP 8.5. Annualizing this impact by taking the midpoint of the projection (2075) and benchmarking it to 2010 points to a 1.19% yr^{-1} reduction.

The combined impact of technological progress and climate change will result in spatially heterogeneous net impacts. Figure 4 illustrates separate county-level annual yield impacts from technology and climate change for the aforementioned climate model and scenario as well as the combined effects. Panels a and b indicate pre- and post-GE trend estimates, whereas panel (c) indicates the gross climate change contribution. Adding the trend estimate to the climate change effect results in the net combined impacts in panels (d) and (e), respectively. The acreage-weighted aggregate trends are 1.02% yr^{-1} (SE = 0.21) for pre-GE technology; 1.61% yr^{-1} (SE = 0.22) for post-GE technology; and $-1.14\% \text{yr}^{-1}$ (SE = 0.10) for climate change. The aggregate combination of the trend plus climate change impacts are -0.12 (SE = 0.24) and 0.47% yr^{-1} (SE = 0.25) for pre- and post-GE, respectively. These results are naturally sensitive to the GCM and the RCP scenario. For example, under the CNRM-CM5 climate model and RCP 8.5 scenario, the combined impacts are 0.25 and 0.90% yr^{-1} for the pre- and post-GE technologies (figure S12). If instead, we hold the GCM fixed and consider the lowest emissions trajectory (i.e. HadGEM2-ES, RCP 2.6), the combined impacts are 0.58 and 1.2% yr^{-1} , respectively (figure S13).



Climate change will severely curtail potential crop yield gains from technological progress in the coming decades based on a wide range of GCMs. Yield projections under all of the GCMs in CMIP5 and RCPs are provided in figure 5 for three different regimes: no yield growth (panel (a)), yield growth comparable to pre-GE era (panel (b)), and yield growth comparable to post-GE era (panel (c)). Under the RCP 8.5 scenario, it will take innovations on the order of the post-GE era to offset climate change impacts. Yield gains less than that, such as those exhibited prior to GE adoption, would lead to reductions in yield levels by the end of the century. Mitigation of CO₂ emissions under the 2.6 and 4.5 RCPs point to a much more optimistic outlook as projected yields would continue to rise through the end of the century under both the pre- and post-GE technological regimes.

4. Discussion and conclusion

US Maize yields exhibit sustained growth since the adoption of hybrid seeds in the 1930s. We find that this growth has accelerated with the adoption of GE seeds, and that this acceleration can only be fully appreciated when accounting for weather patterns which can be confounded with secular technological trends. We cannot identify the biophysical source of this acceleration, but our findings are consistent with yield gains attributed to GE maize adoption in analyses based on both experimental field-trial and actual on-farm yields (Lusk *et al* 2017). While GE traits do not necessarily increase the maximum possible yields (i.e. yield potential), they have been associated with narrowing yield gaps through improved weed control, insect resistance, and more timely planting (Fisher and Edmeades 2010).

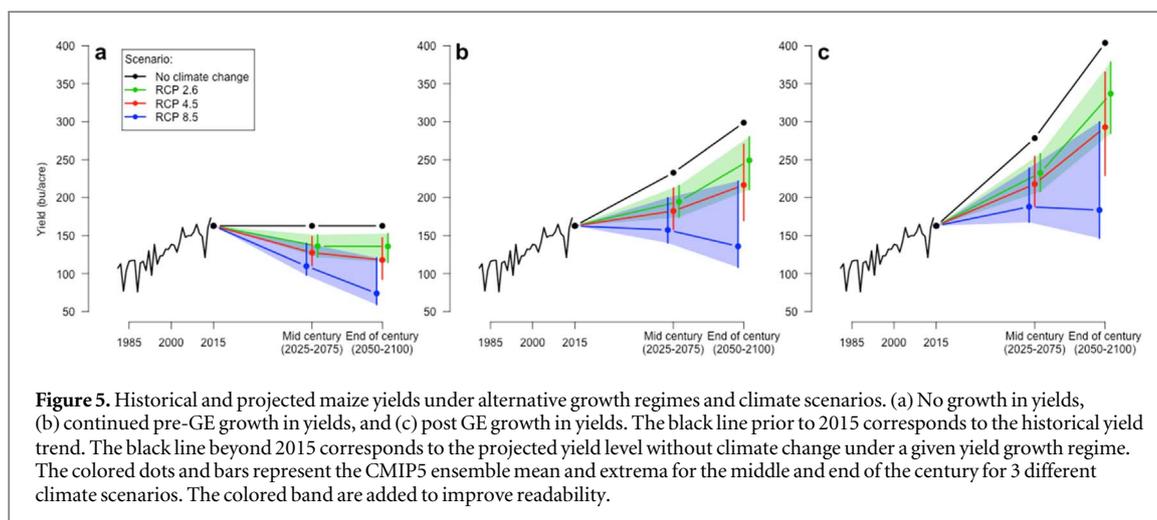


Figure 5. Historical and projected maize yields under alternative growth regimes and climate scenarios. (a) No growth in yields, (b) continued pre-GE growth in yields, and (c) post GE growth in yields. The black line prior to 2015 corresponds to the historical yield trend. The black line beyond 2015 corresponds to the projected yield level without climate change under a given yield growth regime. The colored dots and bars represent the CMIP5 ensemble mean and extrema for the middle and end of the century for 3 different climate scenarios. The colored band are added to improve readability.

(Tollenaar *et al* 2017) that occurred over the sample period (figures S14–S16). Second, our climate change projections do not factor in fertilization effects of increased atmospheric CO₂ levels (Urban *et al* 2015), nor behavioral adaptation to climate change (Butler and Huybers 2013, Burke and Emerick 2016). These additional factors could result in potentially more optimistic impacts.

Author contributions

AOB collected the data and processed the weather variables and climate predictions. JT and AOB contributed equally to all other aspects of the research. Senior authorship is shared equally.

Acknowledgments

AOB was supported by NSF grant 1360424. We thank Carlos M Carrillo for providing the downscaled climate projections.

ORCID iDs

Ariel Ortiz-Bobea  <https://orcid.org/0000-0003-4482-6843>

Jesse Tack  <https://orcid.org/0000-0003-1186-7462>

References

- Alston J M, Beddow J M and Pardey P G 2009 Agricultural research, productivity, and food prices in the long run *Science* **325** 1209–10
- Auffhammer M, Hsiang S M, Schlenker W and Sobel A 2013 Using weather data and climate model output in economic analyses of climate change *Rev. Environ. Econ. Policy* **7** 181–98
- Barrows G, Sexton S and Zilberman D 2014 The impact of agricultural biotechnology on supply and land-use *Environ. Dev. Econ.* **19** 676–703
- Breiman L 1996 Bagging predictors *Mach. Learn.* **24** 123–40
- Burke M and Emerick K 2016 Adaptation to climate change: evidence from US agriculture *Amer. Econ. J.: Econ. Pol.* **8** 106–40
- Butler E E and Huybers P 2013 Adaptation of US maize to temperature variations *Nature Climate Change* **3** 68
- Cassman K G, Grassini P and van Wart J 2011 Crop yield potential, yield trends, and global food security in a changing climate *Handbook of Climate Change and Agroecosystems: Impacts, Adaptation, and Mitigation* (London: Imperial College Press) pp 37–51
- Chavas J P, Shi G and Lauer J 2014 The effects of GM technology on maize yield *Crop Sci.* **54** 1331–5
- Duvick D N and Cassman K G 1999 Post-green revolution trends in yield potential of temperate maize in the North-Central United States *Crop Sci.* **39** 1622–30
- Dyson T 1999 World food trends and prospects to 2025 *Proc. Natl Acad. Sci.* **96** 5929–36
- Evenson R E 1999 Global and local implications of biotechnology and climate change for future food supplies *Proc. Natl Acad. Sci.* **96** 5921–8
- Fischer R A and Edmeades G O 2010 Breeding and cereal yield progress *Crop Sci.* **50** S-85
- Gammans M, Mérel P and Ortiz-Bobea A 2017 Negative impacts of climate change on cereal yields: statistical evidence from France *Environ. Res. Lett.* **12** 054007
- Garrett R D, Rueda X and Lambin E F 2013 Globalization's unexpected impact on soybean production in South America: linkages between preferences for non-genetically modified crops, eco-certifications, and land use *Environ. Res. Lett.* **8** 044055
- Grassini P, Eskridge K M and Cassman K G 2013 Distinguishing between yield advances and yield plateaus in historical crop production trends *Nat. Commun.* **4** 2918
- Greven S and Kneib T 2010 On the behaviour of marginal and conditional AIC in linear mixed models *Biometrika* **97** 773–89
- Hafner S 2003 Trends in maize, rice, and wheat yields for 188 nations over the past 40 years: a prevalence of linear growth *Agric., Ecosyst. Environ.* **97** 275–83
- Jaggard K W, Qi A and Ober E S 2010 Possible changes to arable crop yields by 2050 *Phil. Trans. R. Soc. B* **365** 2835–51
- Klümper W and Qaim M 2014 A meta-analysis of the impacts of genetically modified crops *PLoS One* **9** e111629
- Lobell D B and Asner G P 2003 Climate and management contributions to recent trends in US agricultural yields *Science* **299** 1032–1032
- Lobell D B, Cassman K G and Field C B 2009 Crop yield gaps: their importance, magnitudes, and causes *Annu. Rev. Environ. Resour.* **34** 179–204
- Lobell D B and Field C B 2007 Global scale climate–crop yield relationships and the impacts of recent warming *Environ. Res. Lett.* **2** 014002
- Lobell D B, Hammer G L, McLean G, Messina C, Roberts M J and Schlenker W 2013 The critical role of extreme heat for maize production in the United States *Nat. Clim. Change* **3** 497–501

- Lobell D B, Schlenker W and Costa-Roberts J 2011 Climate trends and global crop production since 1980 *Science* **333** 616–20
- Lusk J, Tack J and Hendricks N 2017 *Heterogeneous yield impacts from adoption of genetically engineered corn and the importance of controlling for weather* Working Paper No: 23519 NBER
- Mosier T M, Hill D F and Sharp K V 2014 30-Arcsecond monthly climate surfaces with global land coverage *Int. J. Climatol.* **34** 2175–88
- Nolan E and Santos P 2012 The contribution of genetic modification to changes in corn yield in the United States *Am. J. Agric. Econ.* **94** 1171–88
- Parisi C, Tillie P and Rodríguez-Cerezo E 2016 The global pipeline of GM crops out to 2020 *Nat. Biotechnol.* **34** 31–6
- Ray D K, Mueller N D, West P C and Foley J A 2013 Yield trends are insufficient to double global crop production by 2050 *PLoS One* **8** e66428
- Ray D K, Ramankutty N, Mueller N D, West P C and Foley J A 2012 Recent patterns of crop yield growth and stagnation *Nat. Commun.* **3** 1293
- Roberts M J, Braun N O, Sinclair T R, Lobell D B and Schlenker W 2017 Comparing and combining process-based crop models and statistical models with some implications for climate change *Environ. Res. Lett.* **12** 095010
- Schlenker W and Roberts M J 2009 Nonlinear temperature effects indicate severe damages to US crop yields under climate change *Proc. Natl Acad. Sci.* **106** 15594–8
- Schmidhuber J and Tubiello F N 2007 Global food security under climate change *Proc. Natl Acad. Sci.* **104** 19703–8
- Shi G, Chavas J P and Lauer J 2013 Commercialized transgenic traits, maize productivity and yield risk *Nat. Biotechnol.* **31** 111–4
- Svitashev S, Schwartz C, Lenderts B, Young J K and Cigan A M 2016 Genome editing in maize directed by CRISPR–Cas9 ribonucleoprotein complexes *Nat. Commun.* **7** 13274
- Tollenaar M, Fridgen J, Tyagi P, Stackhouse P W Jr and Kumudini S 2017 The contribution of solar brightening to the US maize yield trend *Nat. Clim. Change* **7** 275–8
- Urban D W, Sheffield J and Lobell D B 2015 The impacts of future climate and carbon dioxide changes on the average and variability of US maize yields under two emission scenarios *Environ. Res. Lett.* **10** 1–9
- VanWey L K and Richards P D 2014 Eco-certification and greening the Brazilian soy and corn supply chains *Environ. Res. Lett.* **9** 031002
- Wheeler T and Von Braun J 2013 Climate change impacts on global food security *Science* **341** 508–13
- Xu Z, Hennessy D A, Sardana K and Moschini G 2013 The realized yield effect of genetically engineered crops: US maize and soybean *Crop Sci.* **53** 735–45