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

Ariel Ortiz-Bobea, Cornell University, ao332@cornell.edu
Jesse Tack, Kansas State University, jtack@ksu.edu

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

Authors: Ariel Ortiz-Bobea[1*] and Jesse Tack[2]

[1] Charles H. Dyson School of Applied Economics and Management, Cornell University, Ithaca, NY 14853

[2] Department of Agricultural Economics, Kansas State University, Manhattan, KS 66506

[*] Author to whom any correspondence should be addressed. E-mail: ao332@cornell.edu

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Abstract

Predictions of future food supply under climate change rely on projected crop yield trends, which are typically based upon retrospective 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 resulting from the 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 anything short of that will likely induce yield reductions below current levels. Outside of the US, our findings have important implications for regions lagging in the adoption of new technologies – such as GE varieties – 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 (Lobell and Asner 2003, Schmidhuber and Tubiello 2007, Lobell and Field 2007, Lobell *et al* 2011, Cassidy *et al* 2013, Wheeler and von Braun 2013, Butler and Huybers 2013, Lobell *et al* 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 (Duvick and Cassman 1999, Alston *et al* 2013). There has been much work estimating the potential impact of climate change on maize yields using historical data coupled with statistical models (Schlenker and Roberts 2009, Lobell and Asner 2003, 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 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 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, Shi *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. This comparison sheds light on the necessary technological advancements required to offset climate change impacts. Regression 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 anything short of that will likely induce 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.

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. 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 to 50°C, which are necessary to estimate nonlinear 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. 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 (CDL).

2.2 Regression models.

We specify the statistical model using a linear multilevel model:

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

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.

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 nonlinear 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 $(\underline{h}, \ldots, \overline{h})$. Unless otherwise noted, all models in the study rely on an 8th degree polynomial with $\underline{h} = 0$ and $\overline{h} = 36°C$ 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 1,000 times with data resampled with replacement by year. This follows the bootstrap aggregating or "bagging" procedure developed commonly used in machine learning (Breiman 1996).

We utilize out-of-sample forecasting procedures to guide model specification. Within each iteration we randomly sample without replacement 27 of the years (approximately 80% of the data), estimate the model, and then predict yields for the remaining 7 years. We do this 1,000 times and report the mean squared errors of the predictions relative to a baseline model that only includes the random effects for counties and linear time trends, i.e. $y_{it} = u_{0i} + u_{1g}\, year_t + \varepsilon_{it}$.

2.3 Climate projections and impacts

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 and 200 km, which is much coarser than required for our estimates of crop yields. The native GCM data is therefore downscaled based on a modified version of the "delta" method. In the classic implementation of the delta method, coarse resolution GCM anomalies are first interpolated to the finer scale resolution of an observational target grid. Next, these interpolated anomalies are added to historical climatologies, yielding future trajectories at high spatial resolution with changes in the long term mean and variability that are consistent with the coarse resolution of the GCM output.

The fine resolution target is the 4km 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 (4km) 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 $impact_i = 100\{\exp[(\mathbf{z_{1i}} - \mathbf{z_{0i}})\boldsymbol{\gamma} + (\mathbf{p_{1i}} - \mathbf{p_{0i}})\boldsymbol{\beta}] - 1\}$ where $(\mathbf{z_{0i}}, \mathbf{p_{0i}})$ are the baseline temperature and precipitation climate measures and $(\mathbf{z}_{1i}, \mathbf{p}_{1i})$ 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: (i) a single linear trend, (ii) a piecewise linear trend with an inflection point at 1996, and (iii) the same piecewise linear trend but with weather variables added as controls. The latter model provides the best model fit as it improves out-of-sample prediction accuracy relative to other models (Figure S2). Similarly, we find that the placement of the knot at 1996 is optimal (Figure 2).

We find the adoption of GE seeds increased maize yield trends by almost 70 percent. 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

S3-S9). 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 percent per year in each of the two periods, indicating GE seed adoption is associated with a net annual yield growth increase of 0.65 percentage 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 from GE technology over a 22-year period spanning 1996 to the present is approximately 17.5 bushels per acre.

The trend estimates exhibit extensive cross-sectional heterogeneity. Across counties, the pre-GE trends span 0.64 to 1.34 percent whereas post-GE trends range from 1.07 to 2.15 percent with pre-post differences ranging between 0.29 and 1.04 percentage points (Figures S10-S12). 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 percent yield reduction on average across counties for 2050-2100 under the HadGEM2-ES General Circulation Model (GCM) and the business-as-usual representative concentration pathway (RCP) 8.5. Annualizing this impact by taking the midpoint of the projection (2075) and benchmarking it to 2010 points to a 1.19 percent per year 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 percent per year (SE = 0.21) for pre-GE technology; 1.61 percent per year (SE = 0.22) for post-GE technology; and -1.14 percent per year (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 percent per year (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 percent per year for the pre- and post-GE technologies. 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 percent per year, respectively.

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 CO_2 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).

Our results suggest that the relative increase in maize yields has been nonlinear since 1980, with a clear structural change in the growth rate occurring in 1996. Although much recent literature suggests a linear growth trend over many decades for US maize yields (Cassman *et al* 2001, Grassini *et al* 2013), our findings are more in line with studies having identified a nonlinear change in yield trends attributed to GE adoption (Fischer and Edmeades 2010, Xu *et al* 2013, Lusk *et al* 2017). Our analysis suggests that controlling for weather outcomes when estimating yield trends is crucial, and would likely resolve existing debate regarding the appropriateness of linear trend assumptions.

The growth rate of crop yields in the coming decades will have serious implications for the global food supply under climate change. Our results suggest that US maize yields could stagnate under a business-as-usual scenario even with bold assumptions about the sustained growth in crop yields. This has serious implications for other crops and countries as well, as there are many large, economically relevant regions in the world where technology adoption lags and the use of GE crops are prohibited (Barrows *et al* 2014). In addition, GE varieties of rice and wheat are not commercially available. If the relative yield gains estimated here are any indication of the potential for other crops and/or regions, then the adoption of new technologies such as GE varieties may constitute a potentially fruitful adaptation strategy for counterbalancing the effects of climate change. Consumer preferences for (or against) will continue to play a critical role in the global pattern of land-use for production of GE crops and have the potential to alter trade patterns among countries (Garrett *et al* 2013, VanWey and Richards 2014).

Our findings also provide key implications for research and development. Emerging technologies in genome editing as well as an increased emphasis on abiotic stress tolerance (e.g., drought tolerance) could help maintain or even accelerate recent yield growth trends (Svitashev *et al* 2016, Parisi *et al* 2016). In addition, the rise in computing power and fine-scale data collection and analysis may pave the way for a digital revolution that may also contribute to such trends through enhanced precision agriculture. It remains to be seen whether these technological revolutions and the legal framework to reward such innovations and protect intellectual property rights will unfold rapidly enough to counterbalance the projected effects of a changing climate.

Finally, our study has some caveats that bear mentioning. First, our trend analysis attributes a yield growth increase to the adoption of GE seeds but our analysis is unable to identify the biophysical source of this change. There could be other confounding factors that generated yield gains parallel to the introduction of GE maize in the US. We consider the possibility of an increase in solar radiation and find that our results are robust to controlling for increased levels of solar brightening (Tollenaa *et al* 2017) that occurred over the sample period (Figure S15-S17). Second, our climate change projections do not factor in fertilization effects of increased atmospheric CO_2 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.

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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.

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Figures

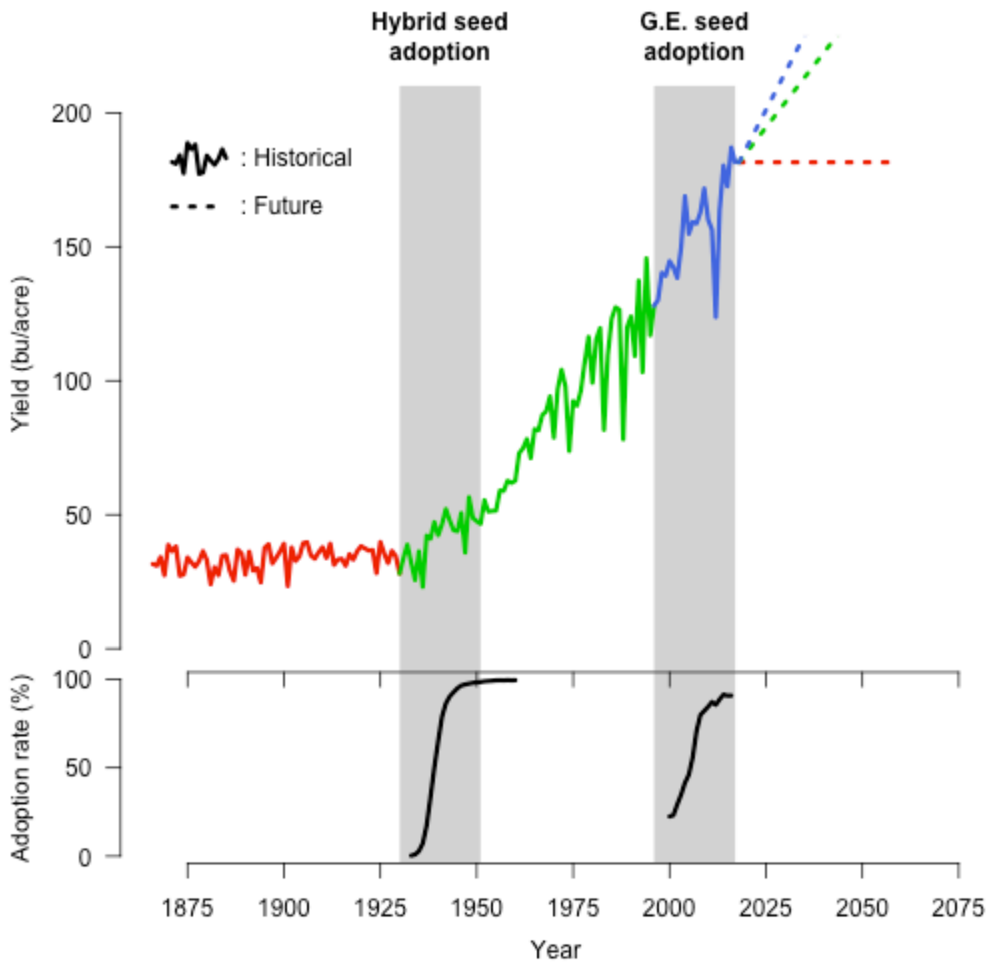

Figure 1. Maize yield trends and technology adoption in the US. The solid line corresponds to historical yields corresponding to 3 regimes: pre hybrid seed (red), pre GE seed (green) and post GE seed (blue). The potential future yields under these historical yield regimes are depicted in dashed lines. The periods of hybrid and GE seed adoption are highlighted with the grey band. The adoption “S”-curves at the bottom correspond to the adoption rate of the corresponding technology (hybrid seed and GE seed).

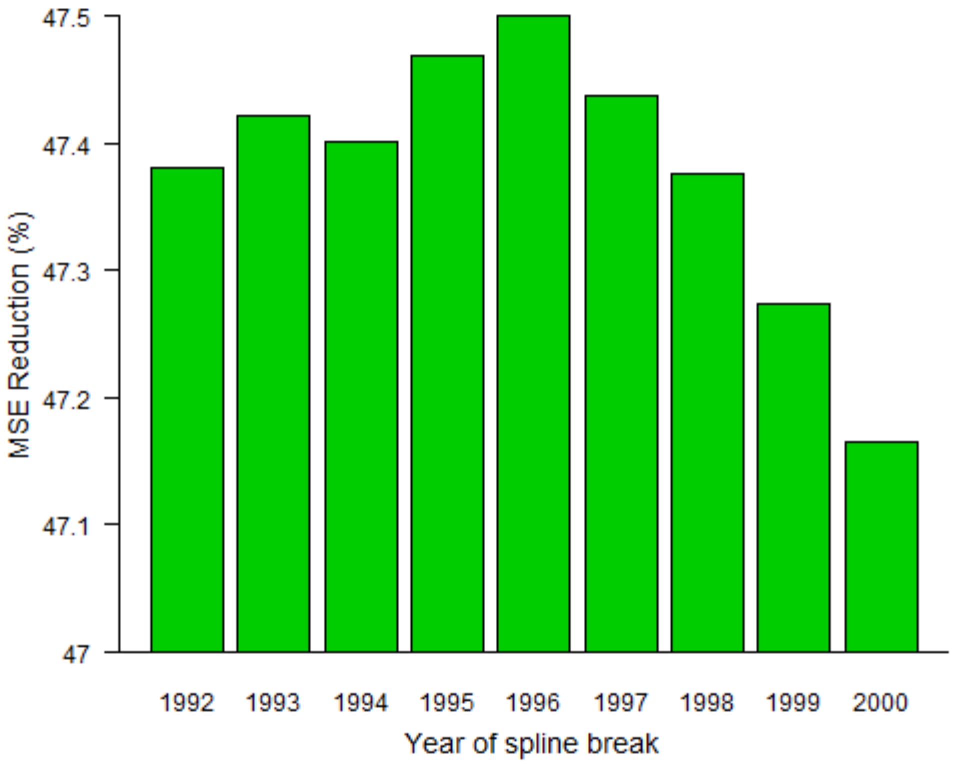

Figure 2. Effect of trend inflexion year on model fit. Each bar corresponds to the reduction in Mean Squared Error (MSE) between a model with an inflexion point in the trend, and a model without an inflexion point or weather variables. The year indicates the year of the inflexion of the estimated trend. A higher number indicates a better model fit.

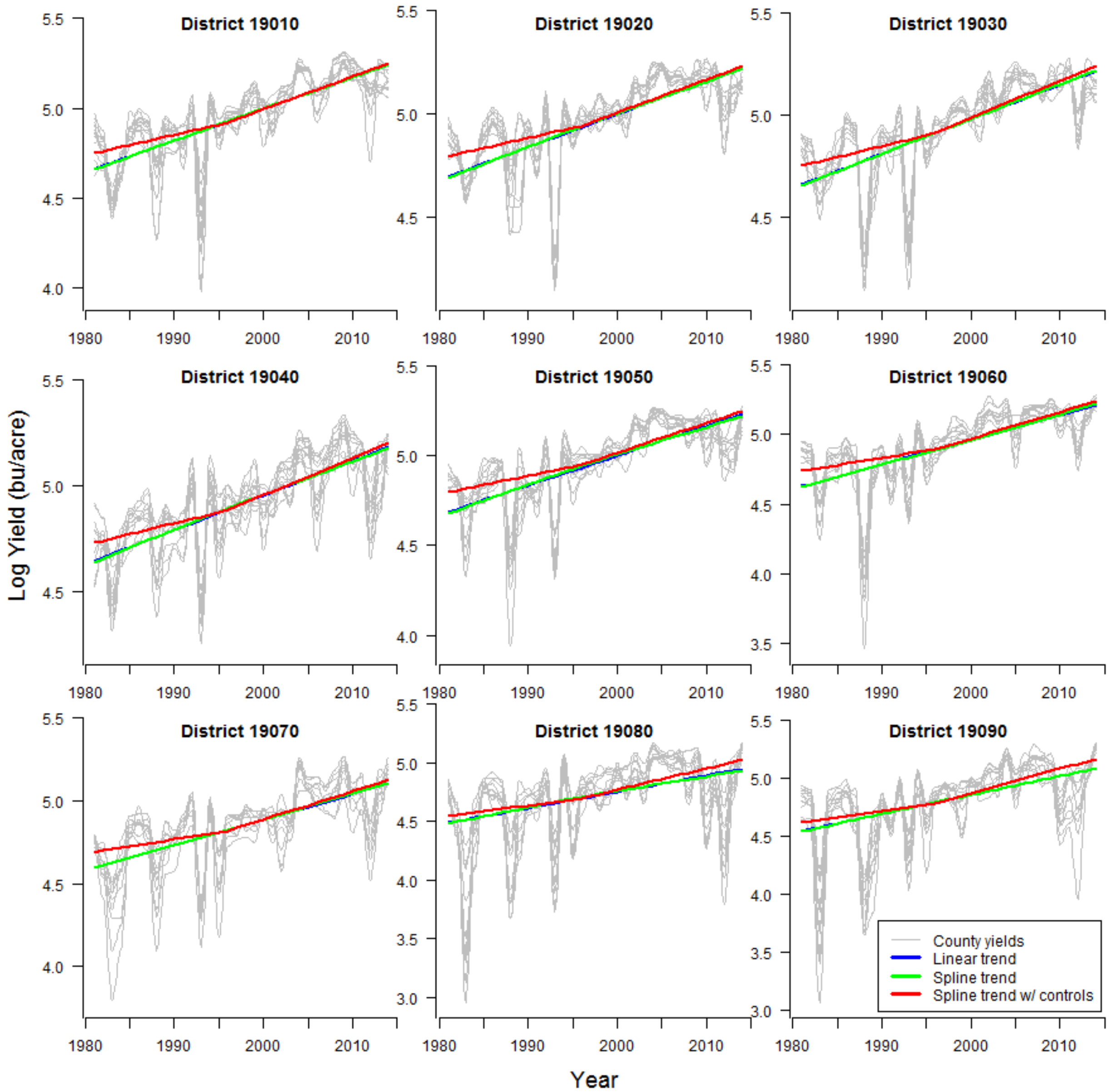

Figure 3. Maize yields and alternative estimated trends by district in Iowa. Each panel portrays yields and estimated yield trends for each agricultural district in the state of Iowa. The grey lines indicate the county-level yields within each district. The blue line represents a linear trend without an inflexion point and without accounting for weather conditions. The green line introduces an inflexion point but does not condition for weather. The red line shows the trend with an inflexion

point that accounts for weather conditions. All inflexion points are set at 1996. Results for other states are presented in the Appendix.

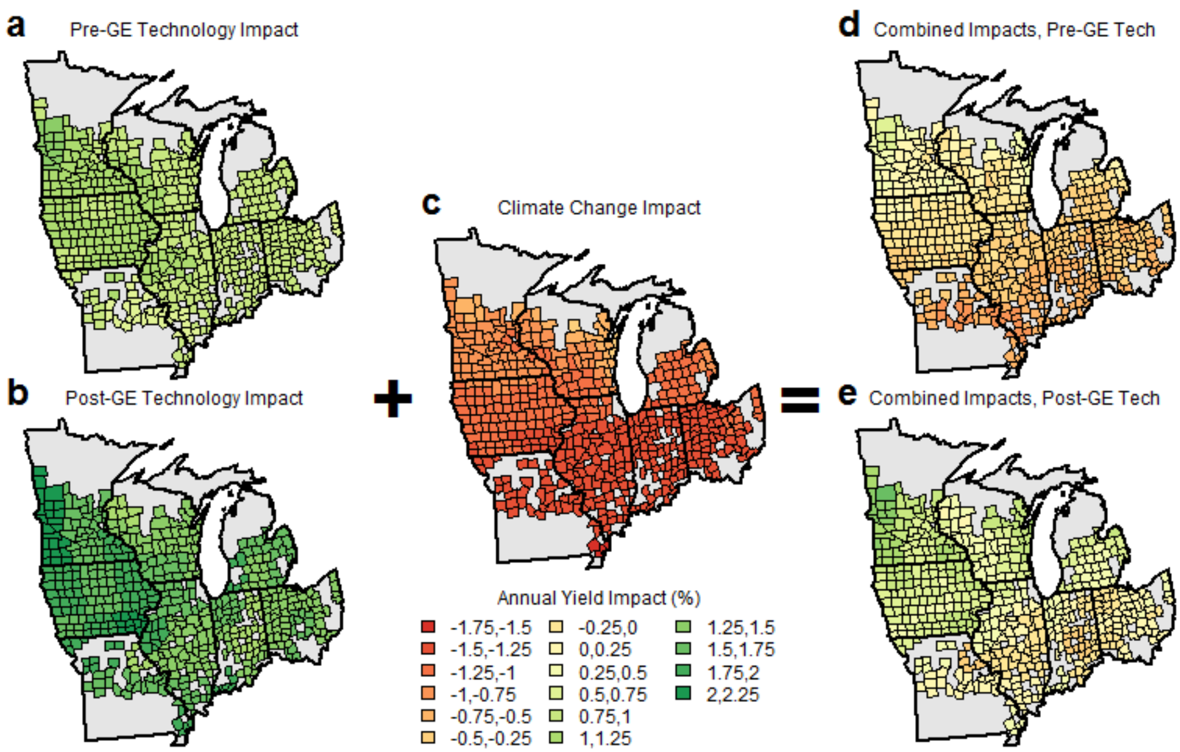

Figure 4. Decomposition of annualized projected yield effects for the Midwest. Each panel corresponds to an annualized percentage yield impact for each county of **a.** technological progress based on the pre-GE trend (1981-1995), **b.** technological progress based on post-GE trend (1996-2014), **c.** the impact of climate change (HadGEM2-ES, RCP 8.5, 2050-2100), **d.** the combined impacts of pre-GE trend and climate change and e. the combined effect of post-GE trend and climate change.

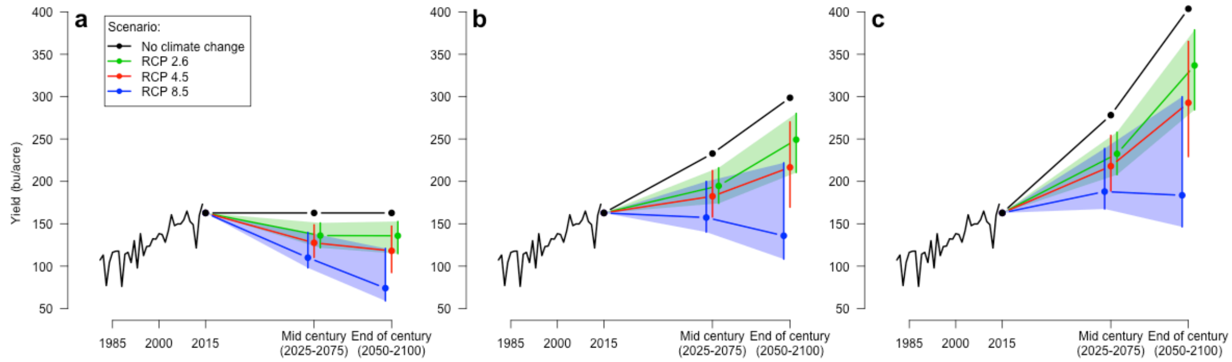

Figure 5. Historical and projected maize yields under alternative growth regimes and climate scenarios. **a.** no growth in yields, **b.** continued pre GE growth in yields, and **c.** post GE growth in yields. The black line prior to 2015 corresponds to the historical yield trend. The black line beyond 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.

Supplemental Material

Figures

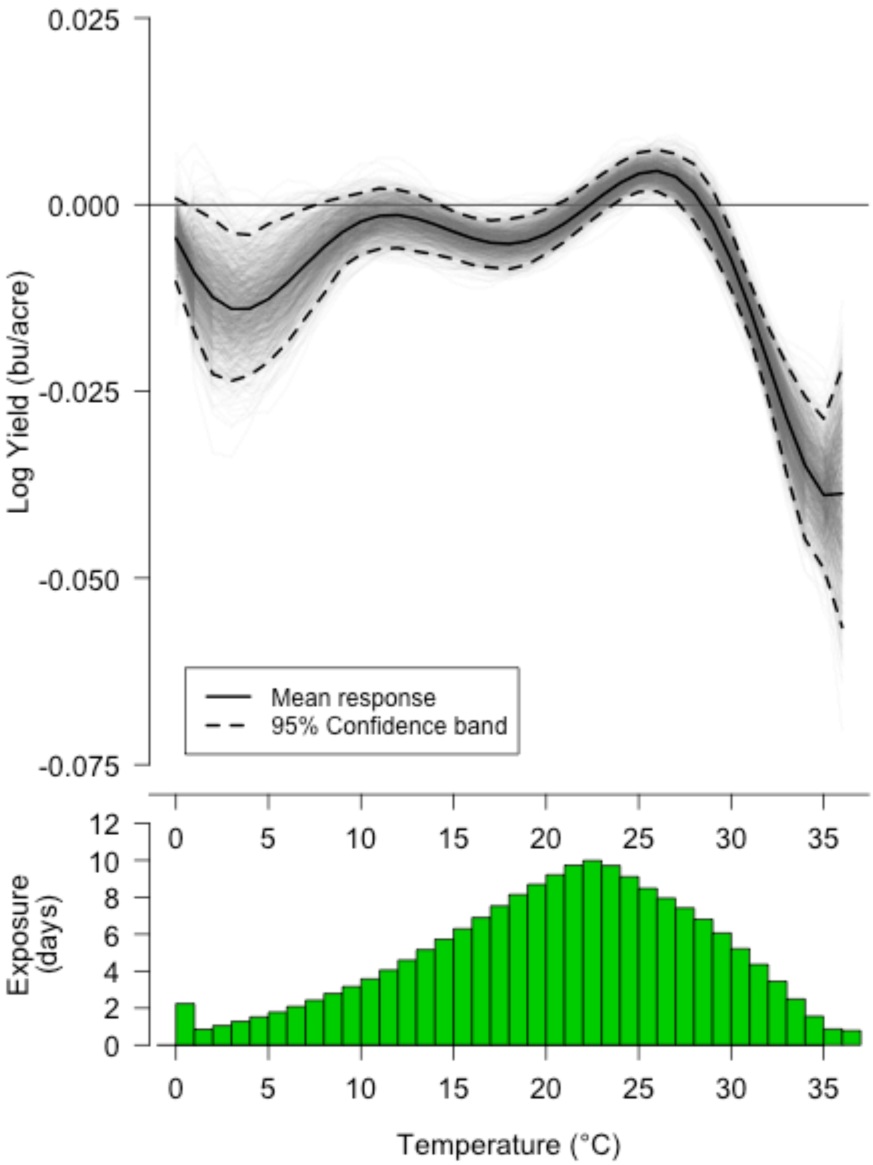

Figure S1. Nonlinear relation between temperature and yields. The top panel display changes in log yield if the crop is exposed for one day to a particular 1°C temperature interval. The 95% confidence band is constructed from a block bootstrapping routine robust to spatial correlation. Histograms at the bottom of each frame display the average temperature exposure among all counties in the data.

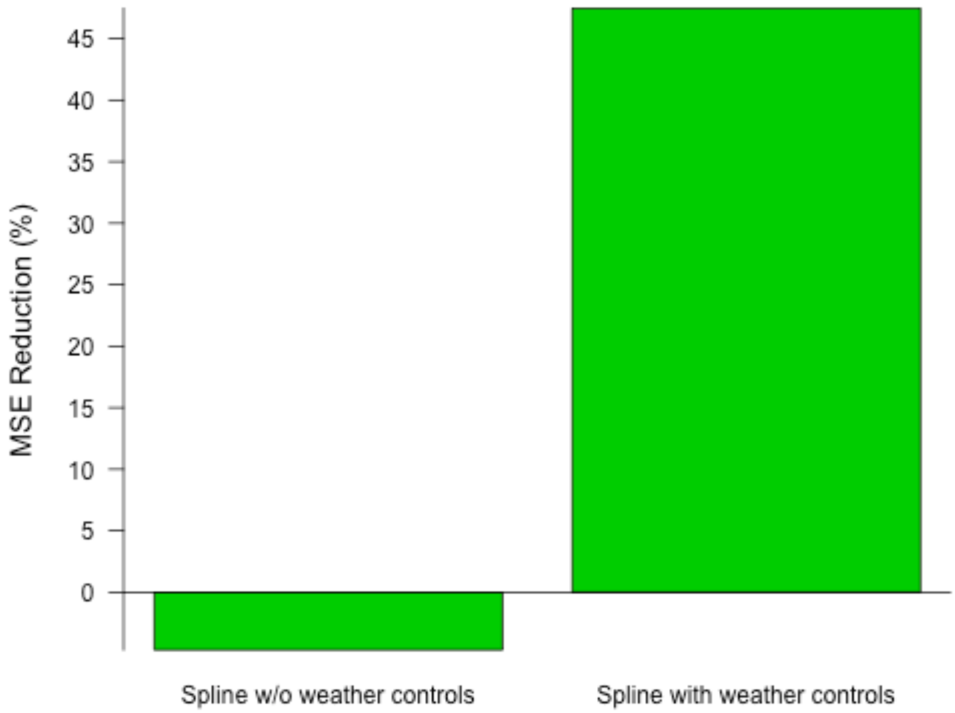

Figure S2. Effect of including weather control variables on model fit. Each bar corresponds to the reduction in Mean Squared Error (MSE) for two models, the first includes a spline trend with an inflection point at 1996 and no control variables, while the second is the same model with variables for temperature and precipitation added as controls. Both report the reduction in MSE relative to a linear trend model. A higher number indicates a better model fit.

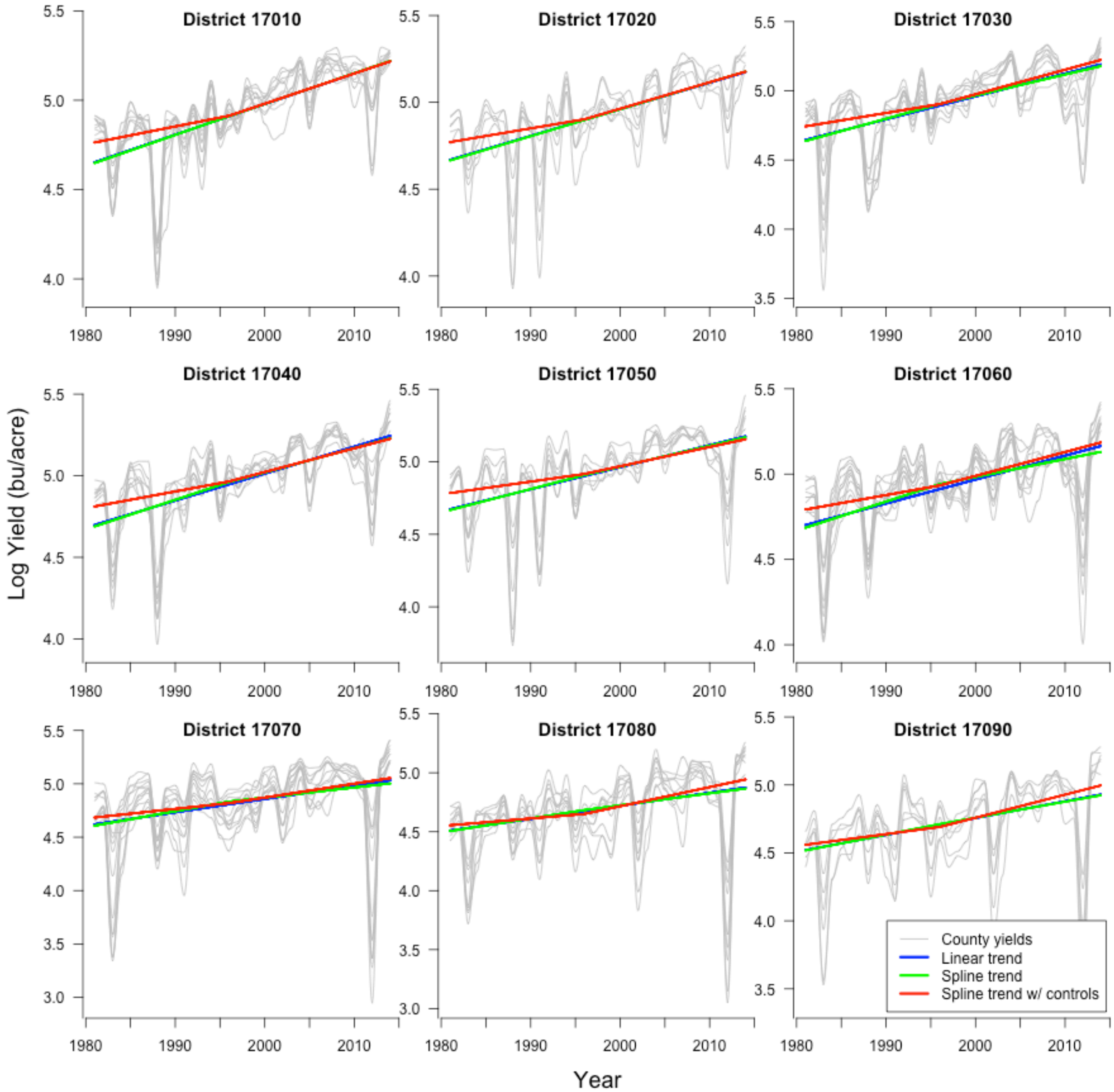

Figure S3. Maize yields and alternative estimated trends by district in Illinois. Each panel portrays yields and estimated yield trends for each agricultural district in the state of Illinois. The grey lines indicate the county-level yields within each district. The blue line represents a linear trend without an inflexion point and without accounting for weather conditions. The green line introduces an inflexion point but does not condition for weather. The red line shows the trend with an inflexion point that accounts for weather conditions. All inflexion points are set at 1996.

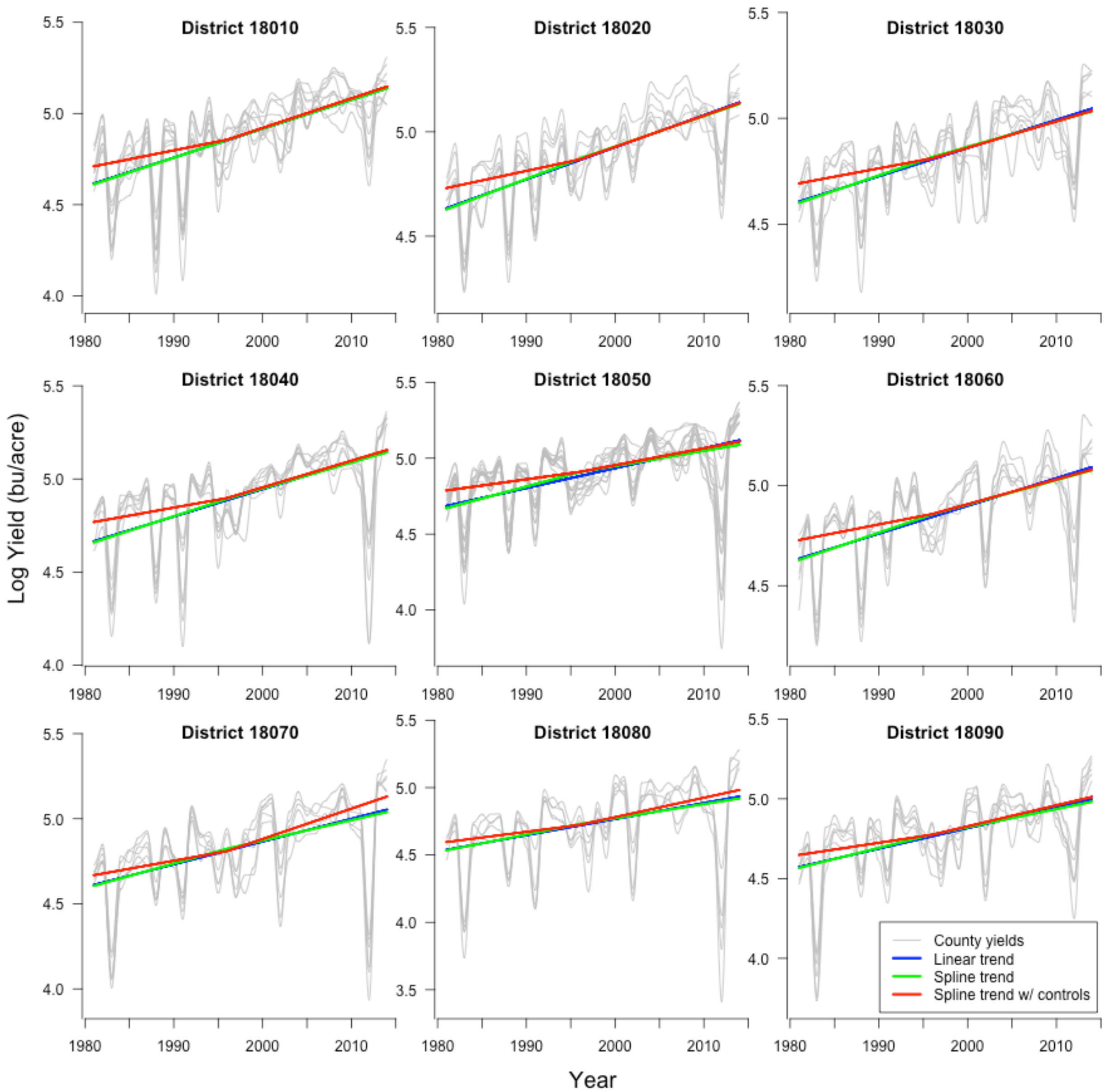

Figure S4. Maize yields and alternative estimated trends by district in Indiana. Each panel portrays yields and estimated yield trends for each agricultural district in the state of Indiana. The grey lines indicate the county-level yields within each district. The blue line represents a linear trend without an inflexion point and without accounting for weather conditions. The green line introduces an inflexion point but does not condition for weather. The red line shows the trend with an inflexion point that accounts for weather conditions. All inflexion points are set at 1996.

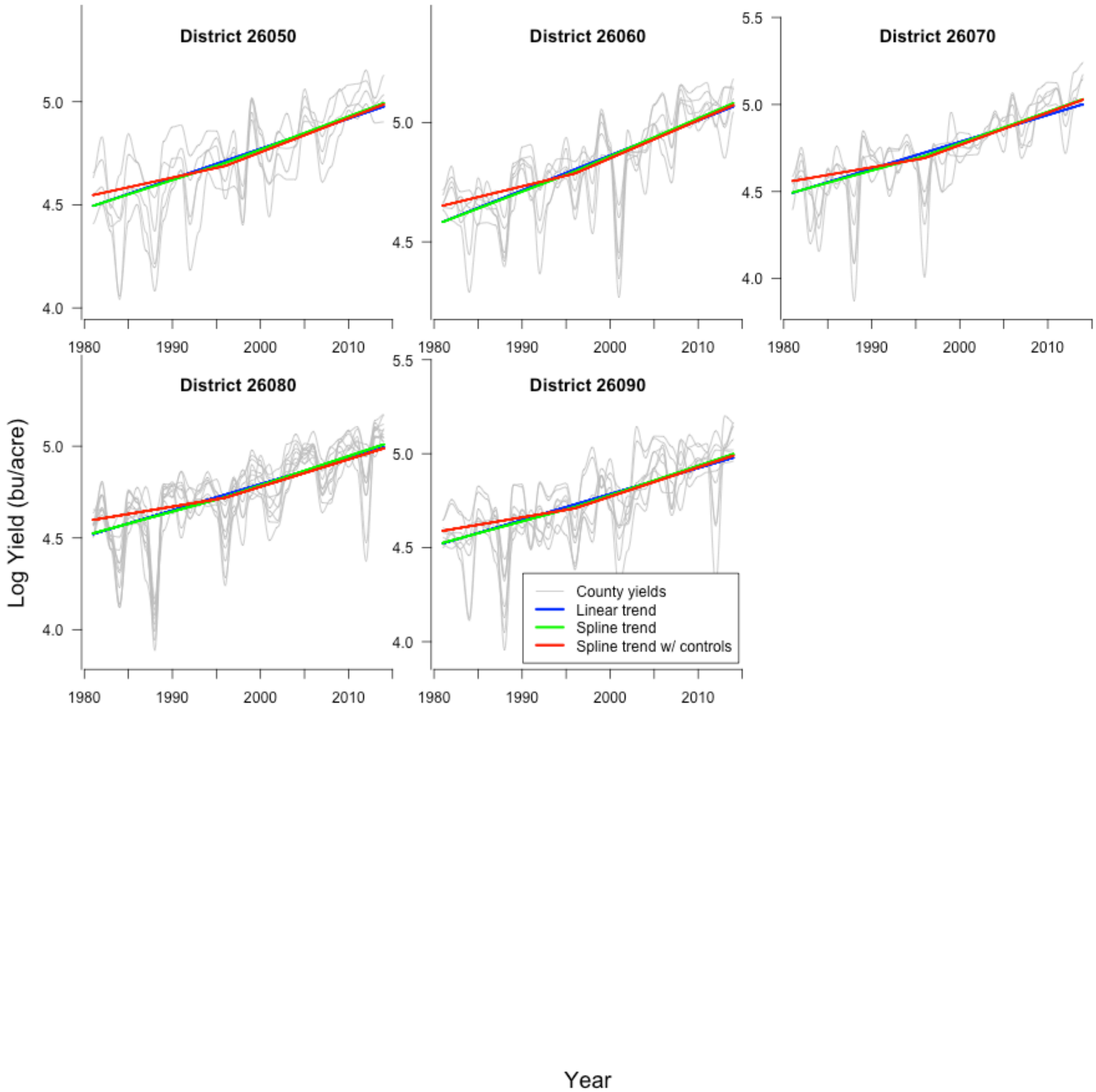

Figure S5. Maize yields and alternative estimated trends by district in Michigan. Each panel portrays yields and estimated yield trends for each agricultural district in the state of Michigan. The grey lines indicate the county-level yields within each district. The blue line represents a linear trend without an inflexion point and without accounting for weather conditions. The green line introduces an inflexion point but does not condition for weather. The red line shows the trend with an inflexion point that accounts for weather conditions. All inflexion points are set at 1996.

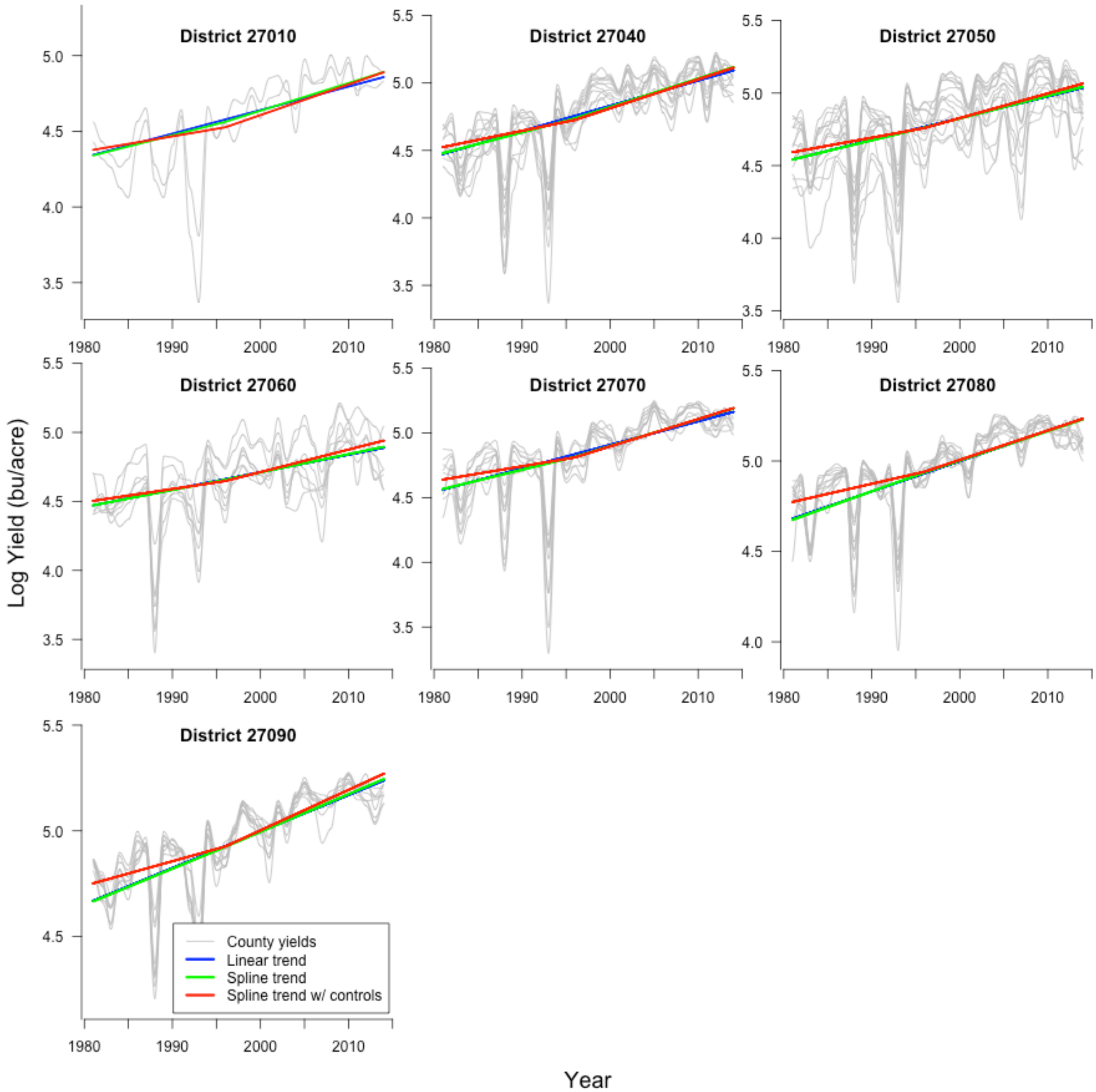

Figure S6. Maize yields and alternative estimated trends by district in Minnesota. Each panel portrays yields and estimated yield trends for each agricultural district in the state of Minnesota. The grey lines indicate the county-level yields within each district. The blue line represents a linear trend without an inflexion point and without accounting for weather conditions. The green line introduces an inflexion point but does not condition for weather. The red line shows the trend with an inflexion point that accounts for weather conditions. All inflexion points are set at 1996.

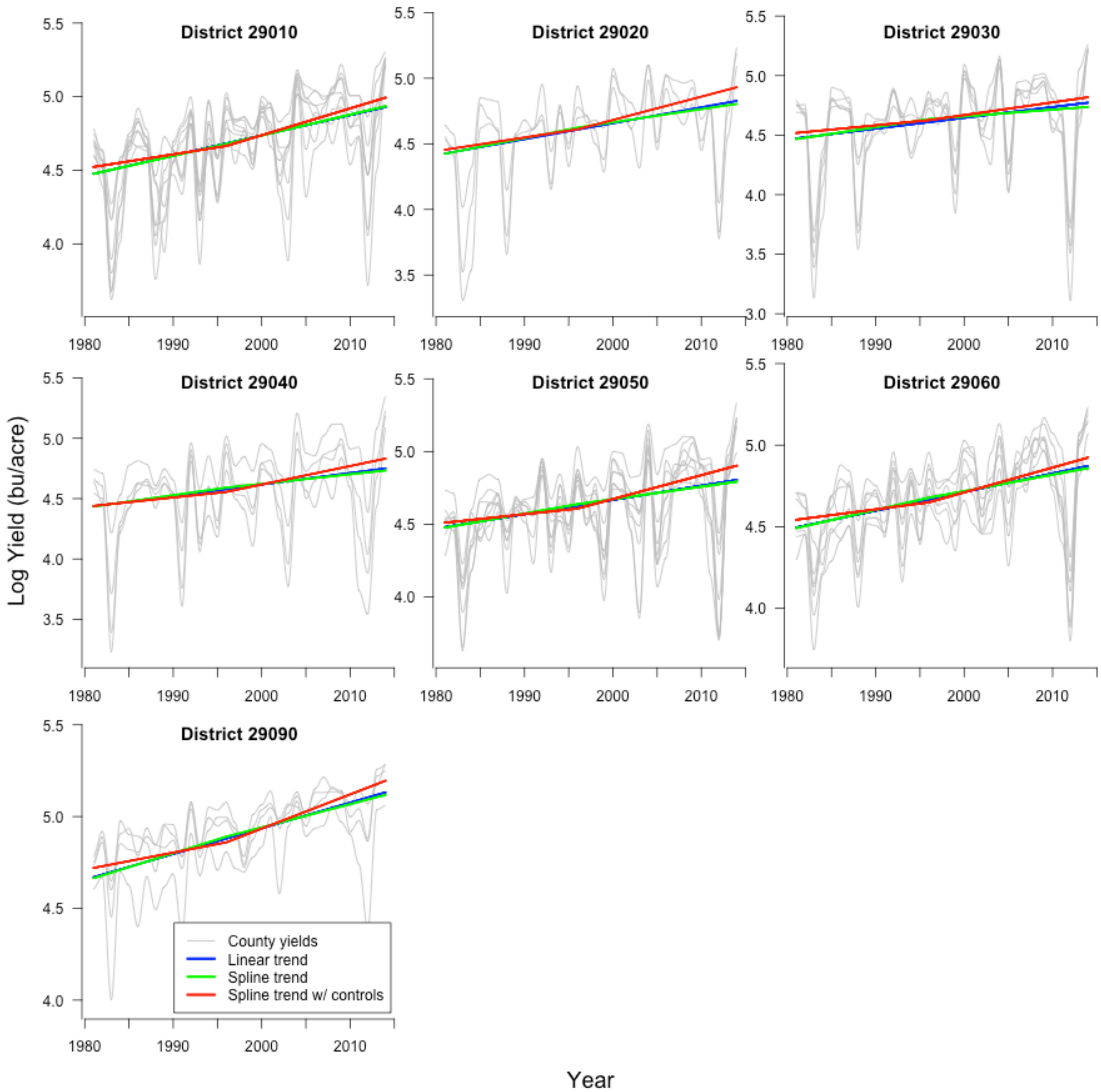

Figure S7. Maize yields and alternative estimated trends by district in Missouri. Each panel portrays yields and estimated yield trends for each agricultural district in the state of Missouri. The grey lines indicate the county-level yields within each district. The blue line represents a linear trend without an inflexion point and without accounting for weather conditions. The green line introduces an inflexion point but does not condition for weather. The red line shows the trend with an inflexion point that accounts for weather conditions. All inflexion points are set at 1996.

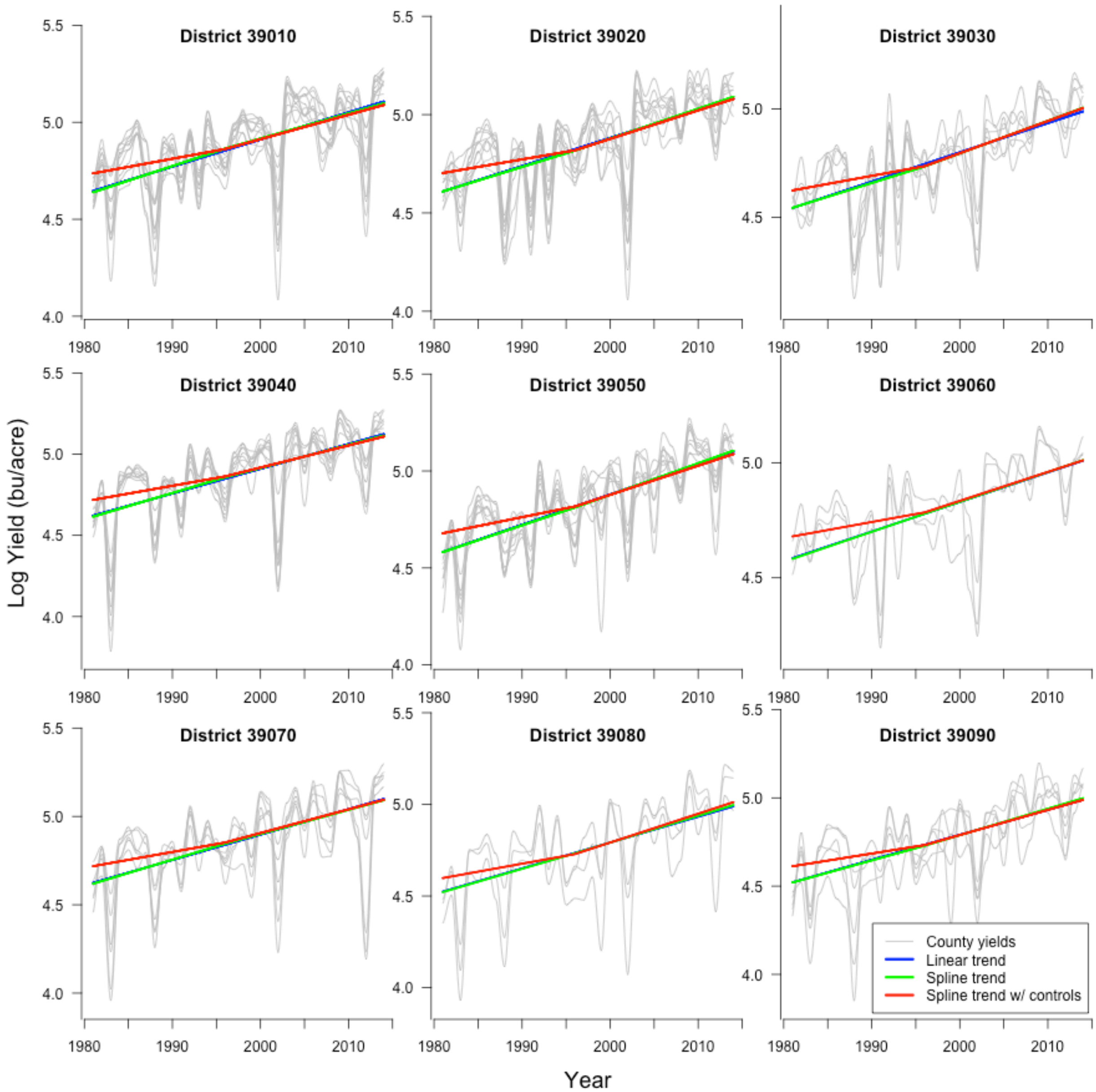

Figure S8. Maize yields and alternative estimated trends by district in Ohio. Each panel portrays yields and estimated yield trends for each agricultural district in the state of Ohio. The grey lines indicate the county-level yields within each district. The blue line represents a linear trend without an inflexion point and without accounting for weather conditions. The green line introduces an inflexion point but does not condition for weather. The red line shows the trend with an inflexion point that accounts for weather conditions. All inflexion points are set at 1996.

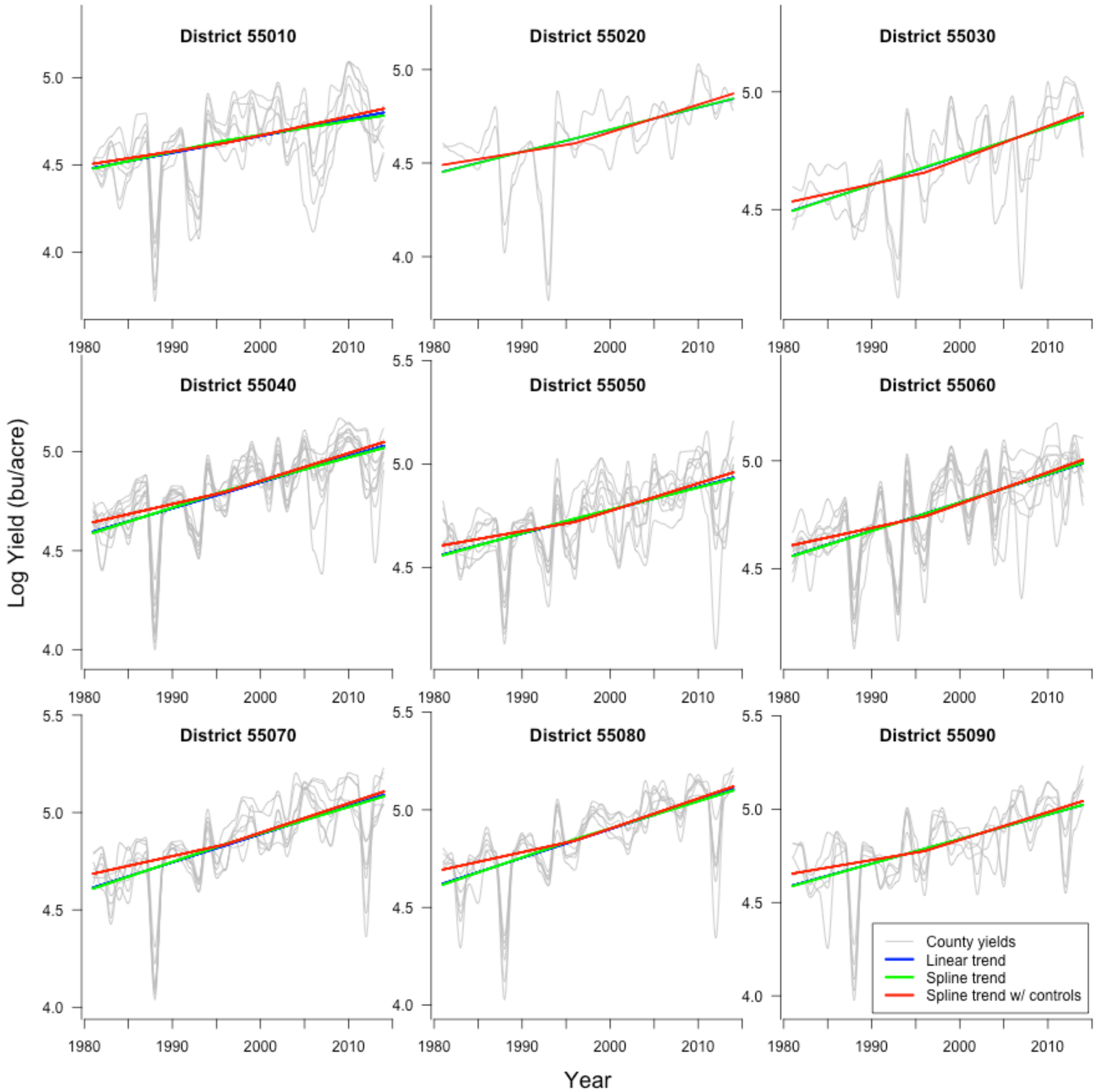

Figure S9. Maize yields and alternative estimated trends by district in Wisconsin. Each panel portrays yields and estimated yield trends for each agricultural district in the state of Wisconsin. The grey lines indicate the county-level yields within each district. The blue line represents a linear trend without an inflexion point and without accounting for weather conditions. The green line introduces an inflexion point but does not condition for weather. The red line shows the trend with an inflexion point that accounts for weather conditions. All inflexion points are set at 1996.

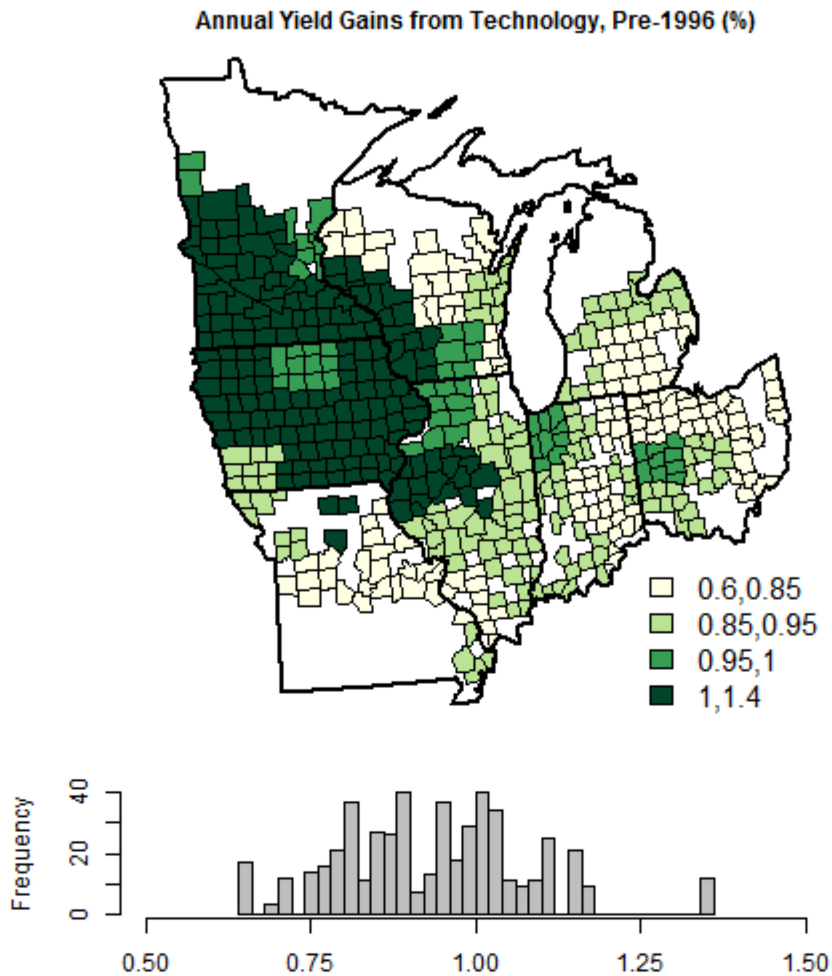

Figure S10. Trend yield estimates for the 1981-1995 period. The preferred model allows for random slopes of the trend in the pre-GE era. The slopes vary by the 64 ag districts in the sample, and reported values are the best liner unbiased predictors (BLUP) of the random trends. The histogram provides the full range of estimates and the map shows how the same values vary spatially.

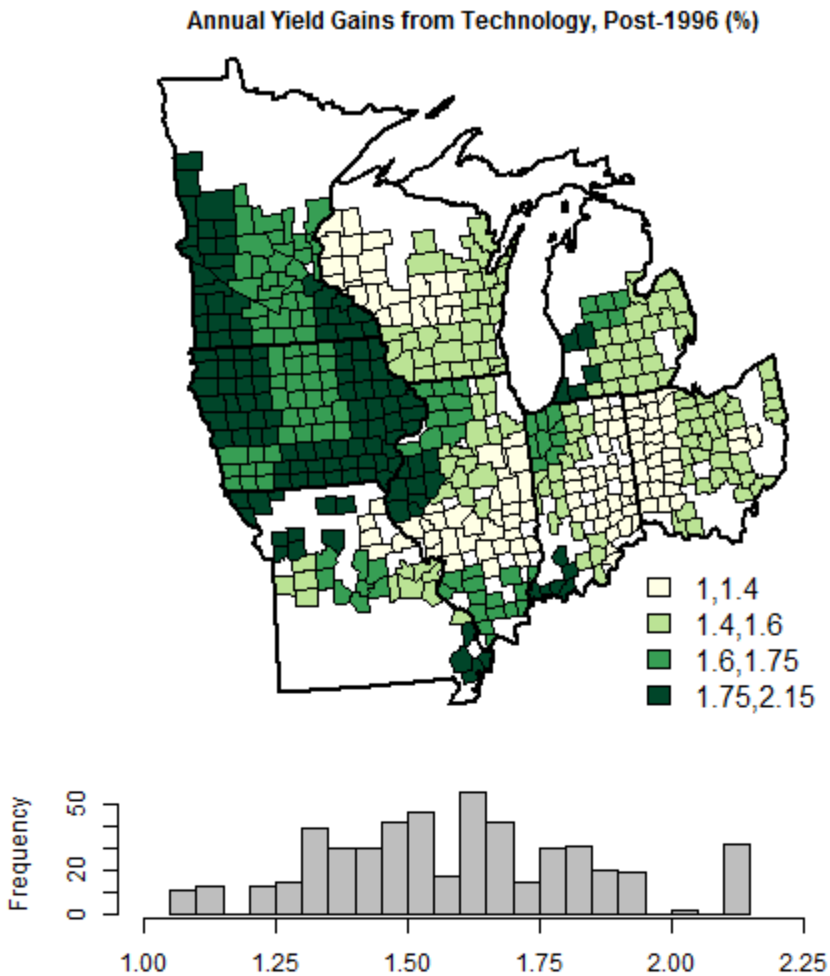

Figure S11. Trend yield estimates for the 1996-2014 period. The preferred model allows for random slopes of the trend in the post-GE era. The slopes vary by the 64 ag districts in the sample, and reported values are the best liner unbiased predictors (BLUP) of the random trends. The histogram provides the full range of estimates and the map shows how the same values vary spatially.

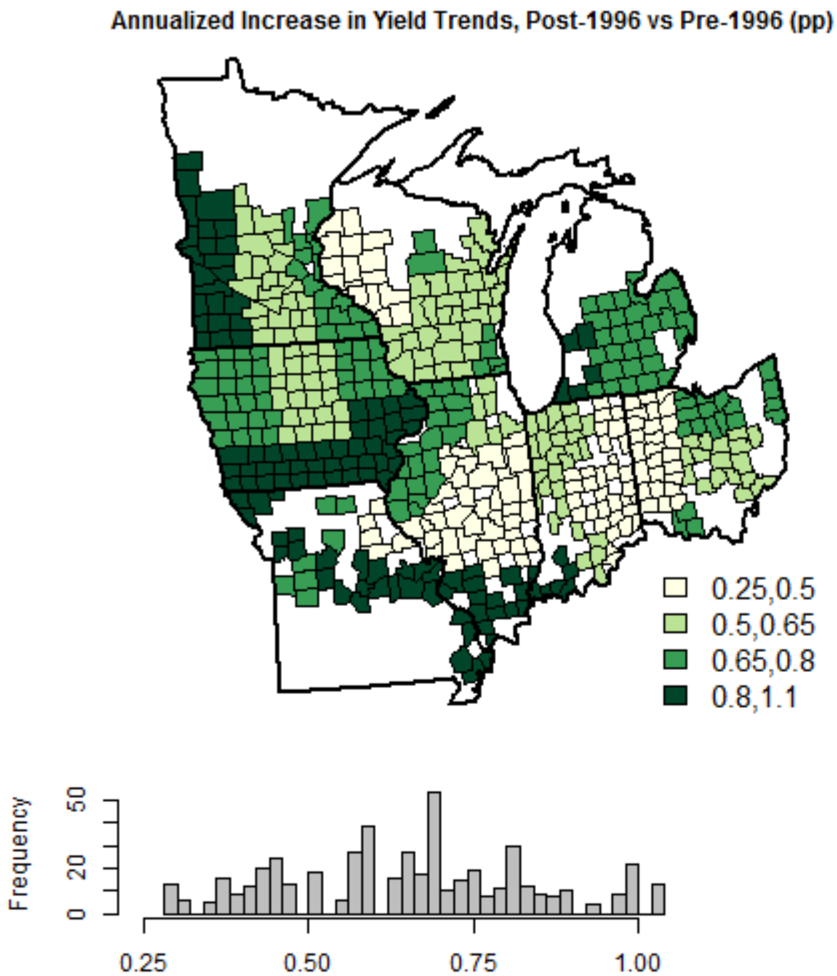

Figure S12. Difference in trend yield estimates for the 1996-2014 versus 1981-1995 periods. Reported values are the simple difference of the trend estimates in post-GE era from Figure S10 less the trend estimates in pre-GE era from Figure S9 The histogram provides the full range of differences and the map shows how the same values vary spatially.

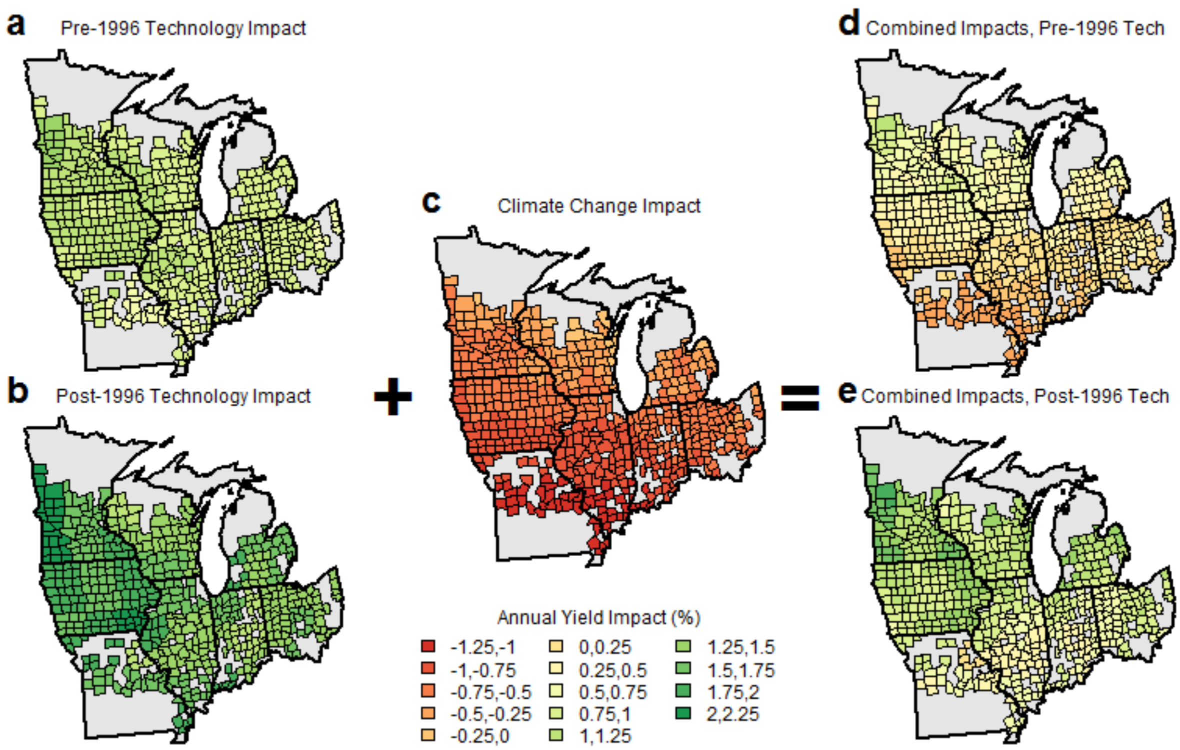

Figure S13. Decomposition of annualized projected yield effects for the Midwest. Each panel corresponds to an annualized percentage yield impact for each county of **a.** technological progress based on the pre-GE trend, **b.** technological progress based on post-GE trend, **c.** the impact of climate change (CNRM-CM5, RCP 8.5, 2050-2100), **d.** the combined impacts of pre-GE trend and climate change and e. the combined effect of post-GE trend and climate change.

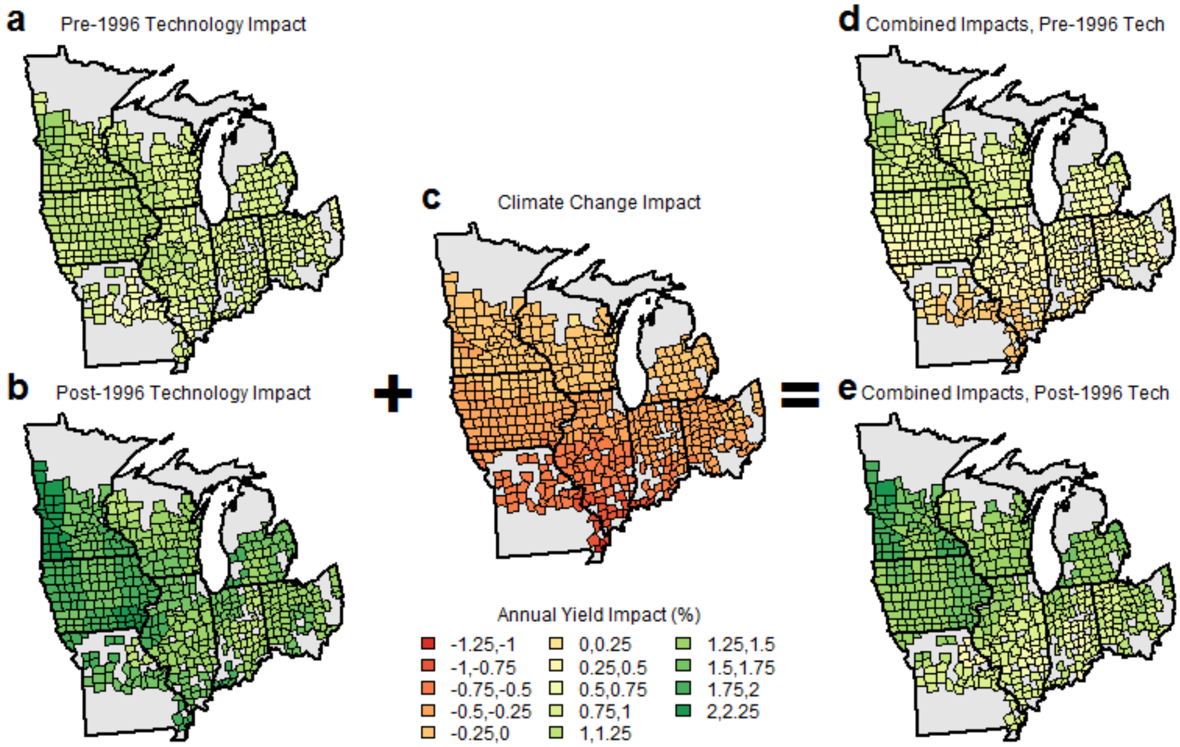

Figure S14. Decomposition of annualized projected yield effects for the Midwest. Each panel corresponds to an annualized percentage yield impact for each county of **a.** technological progress based on the pre-GE trend, **b.** technological progress based on post-GE trend, **c.** the impact of climate change (HadGEM2-ES, RCP 2.6, 2050-2100), **d.** the combined impacts of pre-GE trend and climate change and e. the combined effect of post-GE trend and climate change.

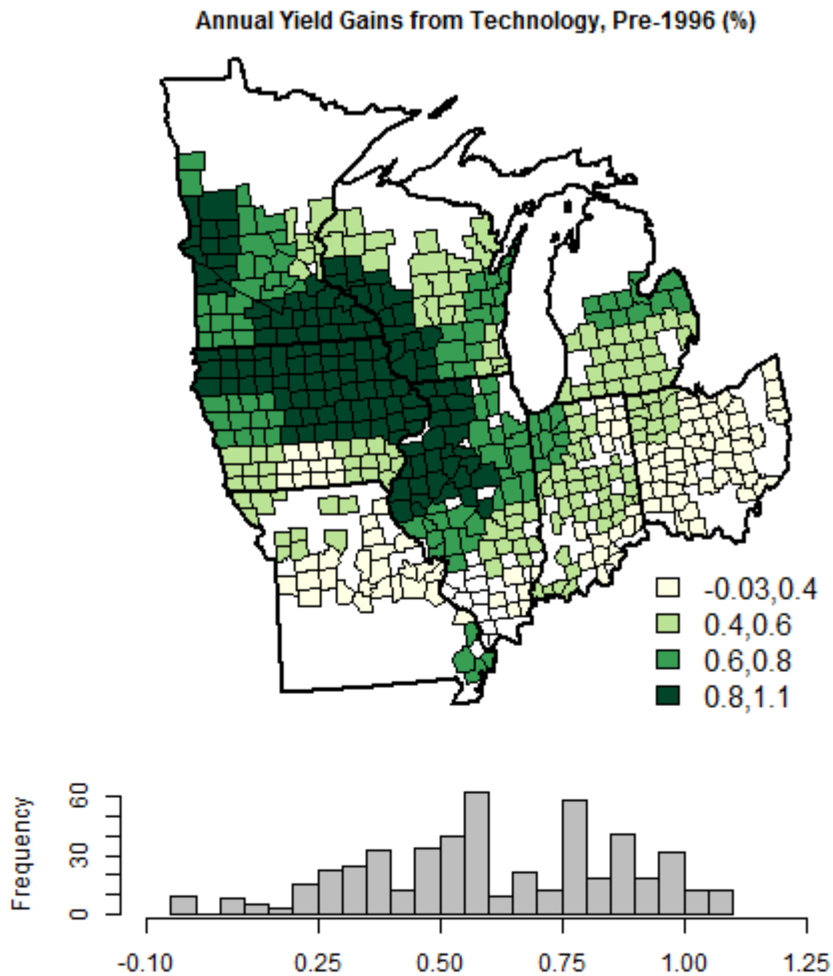

Figure S15. Trend yield estimates for the 1981-1995 period using solar brightening as an additional control. Here we replicate figure S9 for an alternative specification that includes state-level measures of solar brightening as an additional control variable.

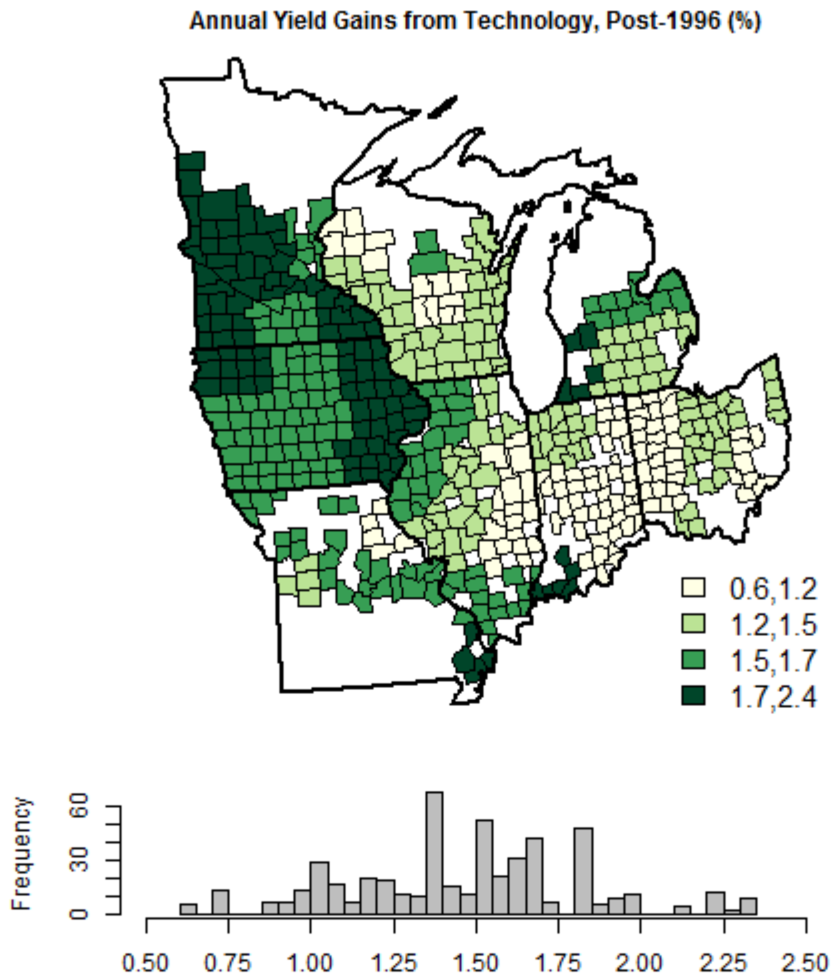

Figure S16. Trend yield estimates for the 1996-2014 period using solar brightening as an additional control. Here we replicate figure S10 for an alternative specification that includes state-level measures of solar brightening as an additional control variable.

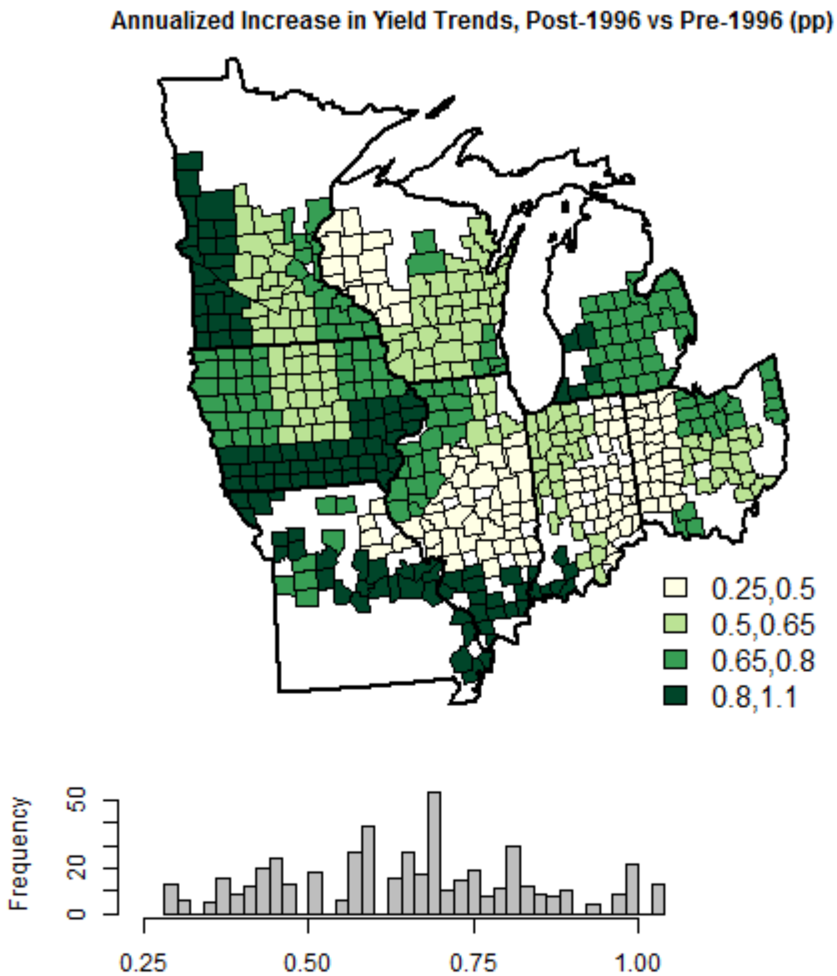

Figure S17. Difference in trend yield estimates for the 1996-2014 versus 1981-1995 periods using solar brightening as an additional control. Here we replicate figure S11 for an alternative specification that includes state-level measures of solar brightening as an additional control variable.

Tables

Table S1. Regression results for multilevel model and panel data model: log maize yield (bu/acre)

Variables	Multilevel Model	Panel Data Model
Temperature variable z_1 (x100)	-3.902	-4.101
	(0.8092)	(0.8529)
Temperature variable z_2 (x100)	-7.226	-7.247
	(0.9202)	(0.9437)
Temperature variable z_3 (x100)	-5.493	-5.487
	(1.088)	(1.066)
Temperature variable z_4 (x100)	-3.418	-3.499
	(1.068)	(1.088)
Temperature variable z_5 (x100)	-2.237	-2.187
	(1.221)	(1.187)
Temperature variable z_6 (x100)	0.1108	0.2260
	(1.177)	(1.126)
Temperature variable z_7 (x100)	-0.8405	-0.7873
	(1.034)	(1.051)
Temperature variable z_8 (x100)	-1.621	-1.330
	(1.030)	(0.9532)
Precipitation p (x100)	0.1265	0.1220
	(0.03247)	(0.0318)
Precipitation squared p^2 (x100)	-0.00012	-0.00012
	(0.000031)	(0.0000305)
Time trend pre-1996 (x100)	0.9140	0.9399
	(0.21587)	(0.2168)
Time trend increase post-1996 (x100)	0.6581	0.6745
	(0.3709)	(0.3808)
Stn dev county RE (x100)	10.30	--
Std dev district RE pre-1996 trend (x100)	0.1736	--
Std dev district RE post-1996 trend increase (x100)	0.2596	--
Observations	17,000	17,000
Counties	500	500
Years	34	34

Notes: The multilevel model is as specified in the methods section. The panel model has the same weather and trend covariates but dummy variables for each county are used instead of county random effects. The panel model assumes homogeneous trends while the multilevel model allows the trends to vary by agricultural districts. Standard errors from a block bootstrap resampling procedure across years are reported in parentheses.