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Supplementary Materials for

Greater Sensitivity to Drought Accompanies Maize Yield Increase in the U.S. Midwest

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Other Supplementary Materials for this manuscript include the following:
(available at www.sciencemag.org/cgi/content/full/344/6183/516/DC)

- Database S1

Materials and Methods

The United States Department of Agriculture (USDA) Risk Management Agency (RMA) data used in this study were obtained from the data warehousing and data mining facility at the Center for Agribusiness Excellence (CAE), Tarleton State University-TAMUS. CAE integrates data from the RMA used in the crop insurance program with information from other sources (weather, soil) for anti-fraud research. Crop insurance data is collected by RMA through private insurance providers who deliver the program. Data (yield, crop loss, geo-location) are at the farm field level and encoded using the common land unit (CLU), which is a geo-located polygon. Aggregated RMA data are available at www.rma.usda.gov and field level data are available upon request from RMA. Although RMA samples only insured farms, this represents the vast majority of Midwest farmers, and comparison of county aggregate yields with official USDA county surveys confirmed the representativeness of our sample (Fig. S12).

Only rainfed fields were considered in this study. To ease computation, a random sample of 100 fields was selected for each county-year combination. The total numbers of field-year combinations used in the study for each state were: Iowa (n = 175,323), Illinois (156,028), Indiana (138,529), Ohio (103,336), Minnesota (101,636), Wisconsin (73,632), Kansas (67,516), South Dakota (65,710), Nebraska (58,049). Thus, the main analysis focused on the 3-I states used 469,880 field-year combinations.

Daily minimum and maximum temperatures and precipitation data were obtained from the PRISM dataset by contract from Oregon State University and integrated into the RMA data. VPD was estimated as the difference between saturated vapor pressure ($0.6107 * \exp(17.269 \times T / (237.3 + T))$) at daily maximum and minimum temperatures.

MARS is a well established data mining approach that has been applied in many disciplines. It can be viewed as a generalization of stepwise linear regression, but instead of simple linear functions as a basis it uses piecewise linear functions, which allows the model to efficiently capture asymmetries and nonlinearities. As candidate predictors for the model, we use Tmin, Tmax, Prec, and VPD averaged over five successive 30 day periods spanning from 30 days before sowing to 120 days after sowing. This allows the model to capture differential weather sensitivities at different development stages. Finally, predictors are included for year and sowing day, with the former intended to capture effects of non-weather related trends that could bias estimates of weather effects, and the latter intended to capture the effects of sowing date not reflected in the change in weather exposure. For example, late sowing could be associated with selection of shorter maturing cultivars that have lower yields, and omitting sowing date would result in potential bias in weather coefficients. MARS was implemented with the Earth package in R with degree = 2, which allows for interactions between variables although no interaction terms were selected.

A supplementary analysis using PDSI, instead of VPD, was conducted using PDSI computed based on the code provided in (28) with a weather record length of 1950-2012. Water holding capacity in the top 100cm of soil at each location was obtained from the SSURGO database provided by the Natural Resources Conservation Service.

APSIM simulations were performed for Johnston, Iowa with APSIM-Maize Version 7.5 following (17). Plants were sown on May 8 of each year with 300 kg of N fertilizer applied, and on soils with water holding capacity of 330 mm, filled 80% at sowing. The cultivar Pioneer_3394 was used in all simulations, as it is representative of varieties grown in this region during the study period.

To estimate future VPD changes, monthly Tmax and specific humidity output were obtained for 29 climate models reporting both variables for RCP8.5 in the Coupled Model Intercomparison Project Phase 5 (CMIP5). RCP8.5 corresponds to a relatively high rate of greenhouse gas emissions, although projections from other emission scenarios do not significantly differ over the time frame of this study (to mid-century). Tmax and specific humidity were first averaged for all grid cells in study region for each month. Nine-year averages for July were then calculated centered on 2010, 2020, etc., with July corresponding roughly to the key period of 61-90 DAS. Average daily VPD was calculated as 0.75 * (VP(Tmax) – Ea), where VP(Tmax) corresponds to saturated vapor pressure for Tmax, and Ea is the actual vapor pressure at sea level, calculated from specific humidity (q) as 101.3 * q / 0.622 (*29*). Changes in VPD for each climate model from the 2010 baseline were then added to the observed average VPD over the study region.

Additional Database S1 (separate file)

Field-level data on maize and soybean yields, sow dates, and associated weather variables used in this study. One hundred fields were randomly sampled from each county in each year, with a different random sample used each year. All information that could be used to identify individual producers, such as latitude and longitude, has been removed to comply with USDA policies on personal identifiable data. Dataset is available at Science Online. Identical files are also accessible at http://purl.stanford.edu/tp790js7917.

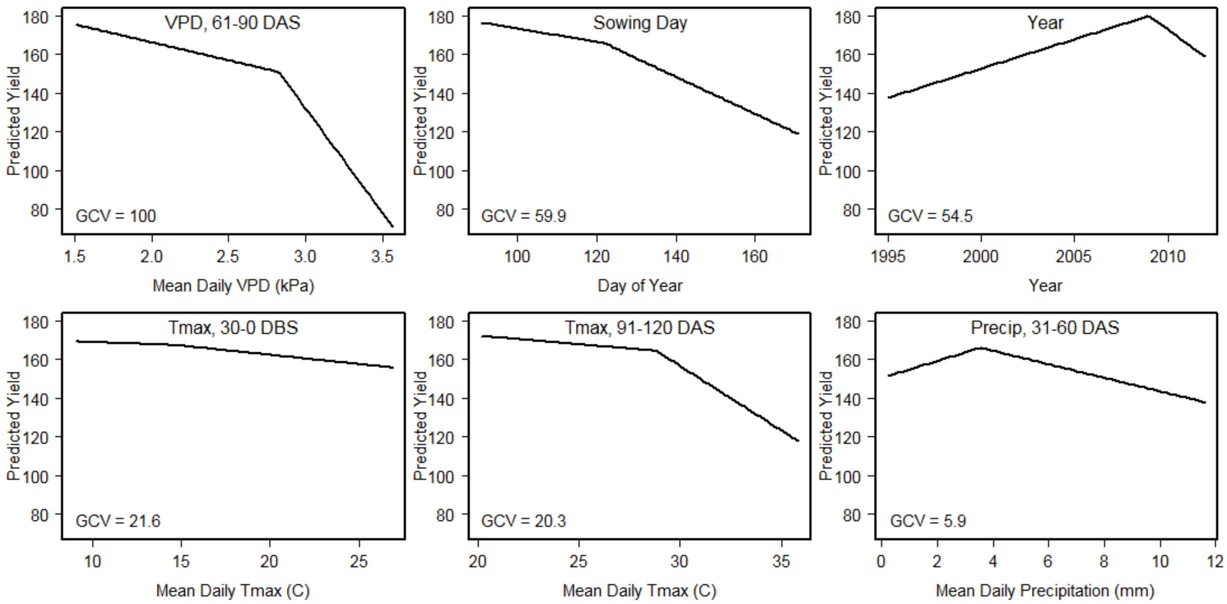

Fig. S1.

Maize yield response to weather. Summary of the response curves of the MARS model fit to the maize data for Iowa, Illinois, and Indiana. Six variables were selected by the model, and each panel indicates the predicted yield (Bu/Ac) for each value of that variable, holding all other variables at their median value. GCV indicates a measure of relative variable importance, which is the average decrease in generalized cross validated error when the variable is added to a model. GCV values are scaled so that the most important variable has a GCV equal to 100.

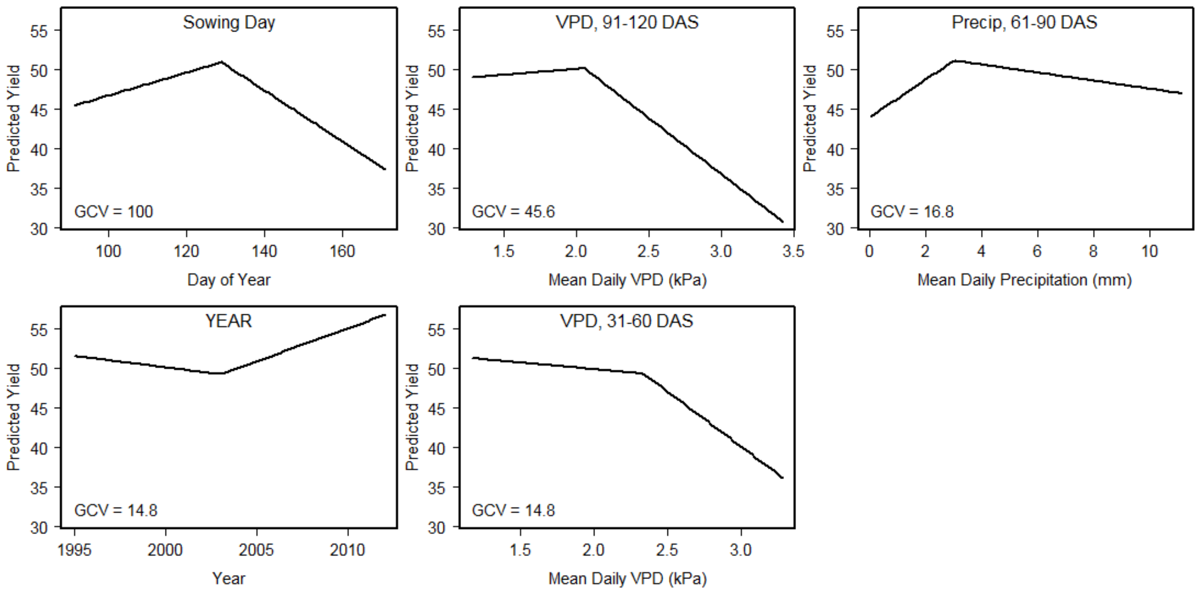

Fig. S2

Summary of the response curves of the MARS model fit to the soybean data for Iowa, Illinois, and Indiana. GCV indicates a measure of relative variable importance, which is the average decrease in generalized cross validated error when the variable is added to a model. GCV values are scaled so that the most important variable has a GCV equal to 100.

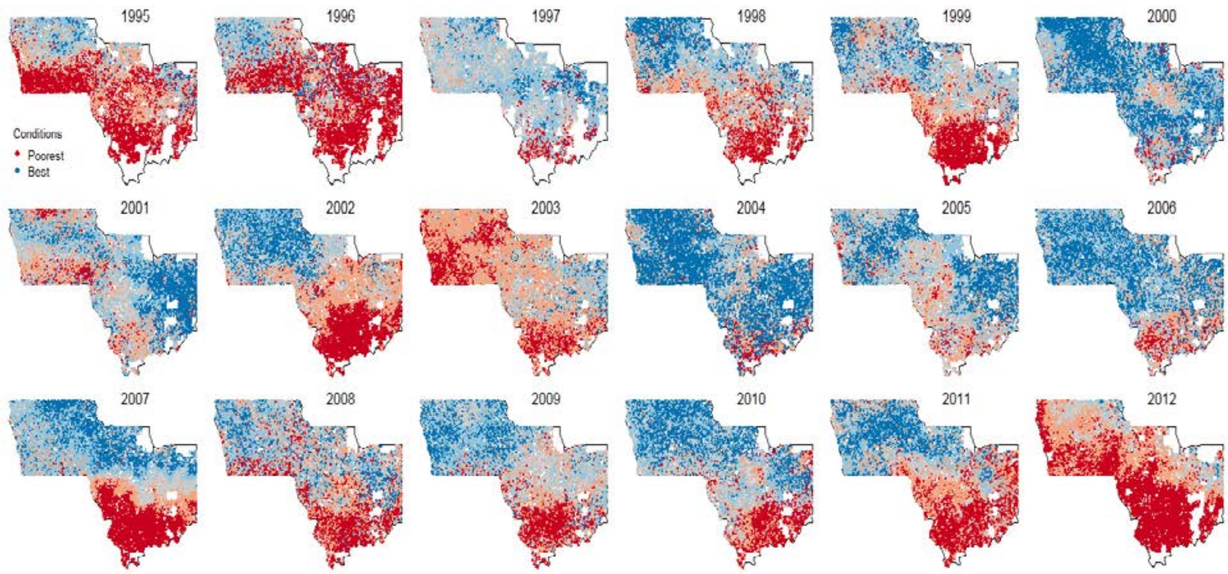

Fig. S3

The locations of Environment Index quintiles for soybean for each study year. Red indicates the lowest EI values, indicating the worst yield conditions, and blue indicates best yield conditions.

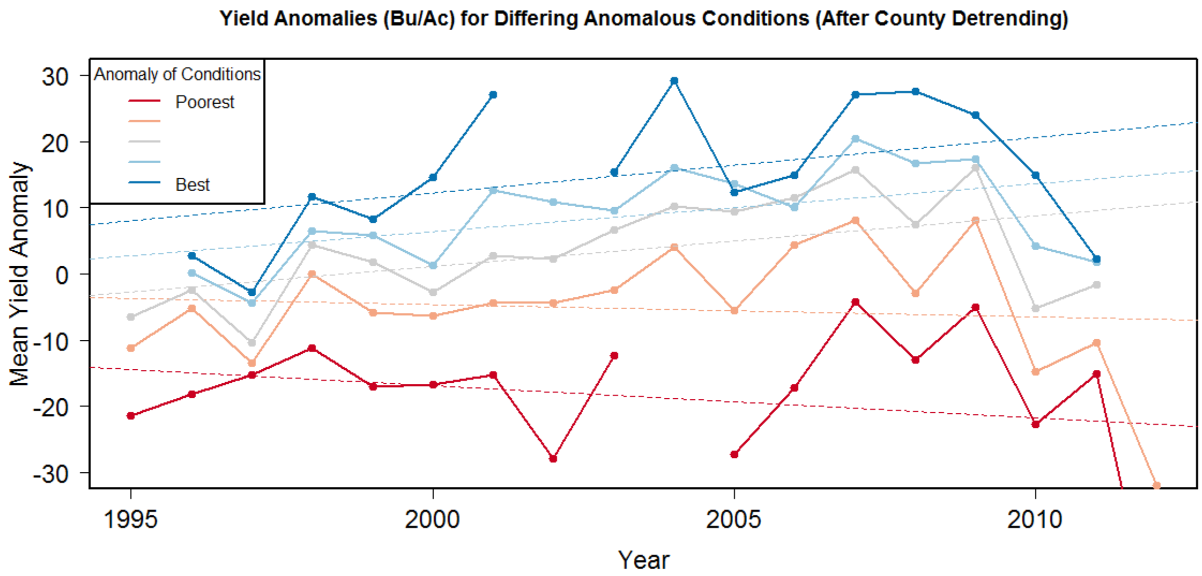

Fig. S4

Average maize yield anomalies (Bu/Ac) for quintiles of EI anomaly by year. Dashed lines show best-fit linear regression for each quintile. This is the same as Fig. 2b in main paper, but uses county-detrended data for both observed yields and EI, which controls for any possible omitted variables that cause mean yields or yield trends to differ by county.

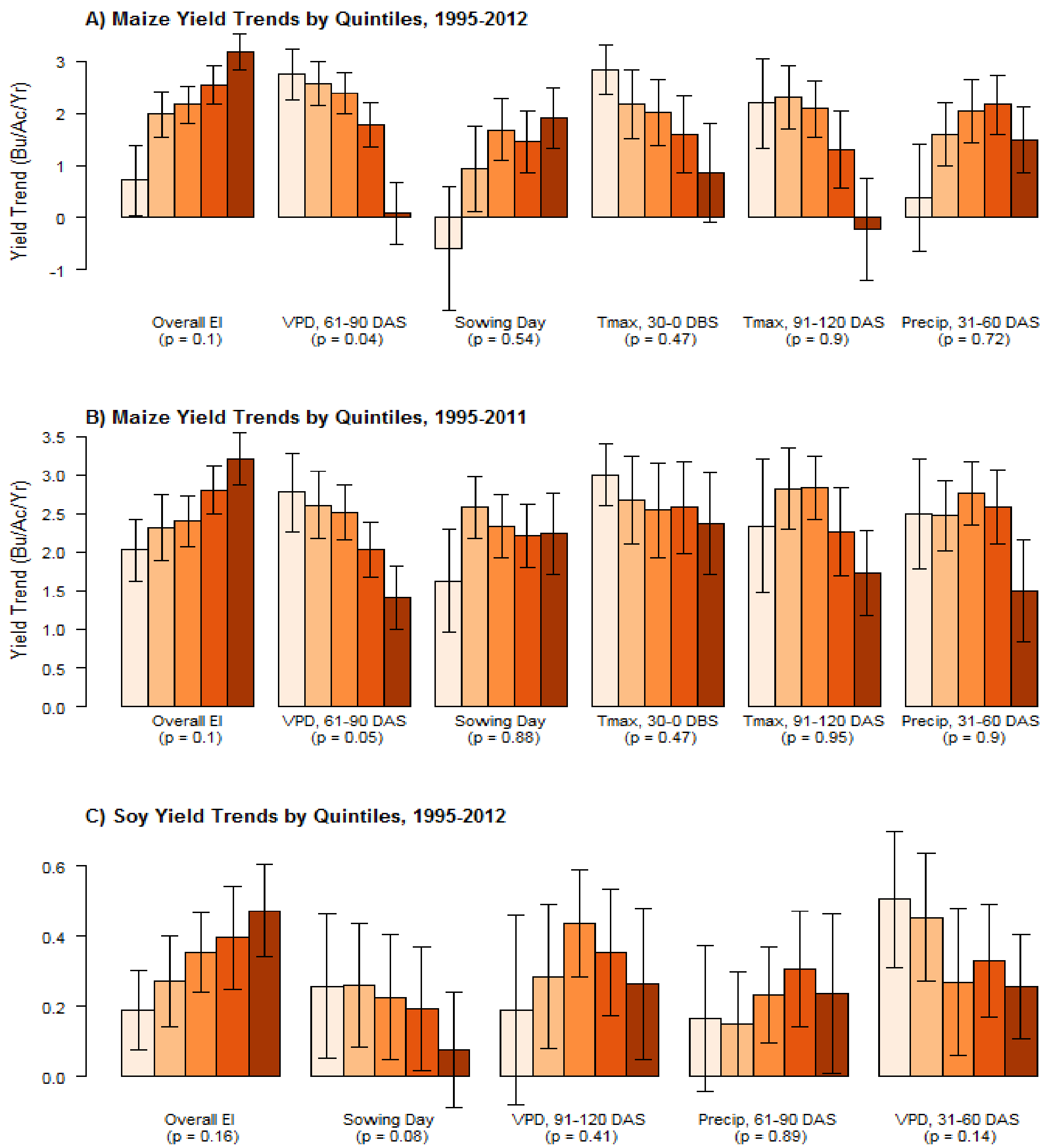

Fig. S5

(a-b) Maize and (c) soybean yield trends by quintile of EI and each component of EI. P values refer to the significance of time trend of difference between highest and lowest quintile, with p<0.05 deemed significant. (b) shows results for maize when excluding 2012 from the trend analysis.

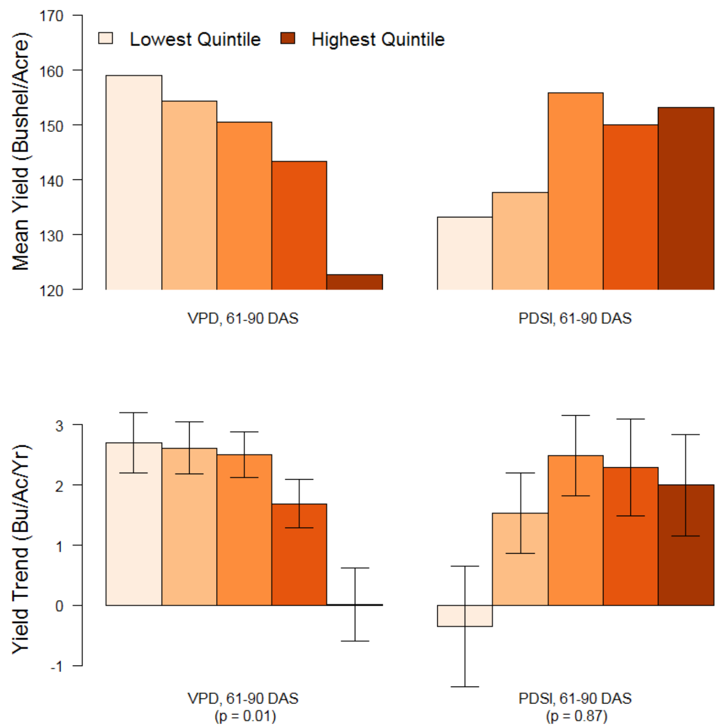

Fig. S6

A comparison of average maize yields (top) and yield trends for 1995-2012 (bottom) for different quintiles of VPD and Palmer Drought Severity Index (PDSI) for 61-90 days after sowing. Low values of PDSI correspond to more drought stress, and have lower average yields. However, yields for the highest quintile of VPD are lower, on average, than for the lowest quintile of PDSI, indicating that VPD is a better discriminator of yields. Similar to results for VPD, yield trends are lower for the quintiles of PDSI with more drought stress. However, the time trends of yield differences between the highest and lowest PDSI quintile are not statistically significant. This comparison was done with a different random sample of fields than in main paper, which is why p-value for VPD trends is slightly different than in Fig. 3 of main paper.

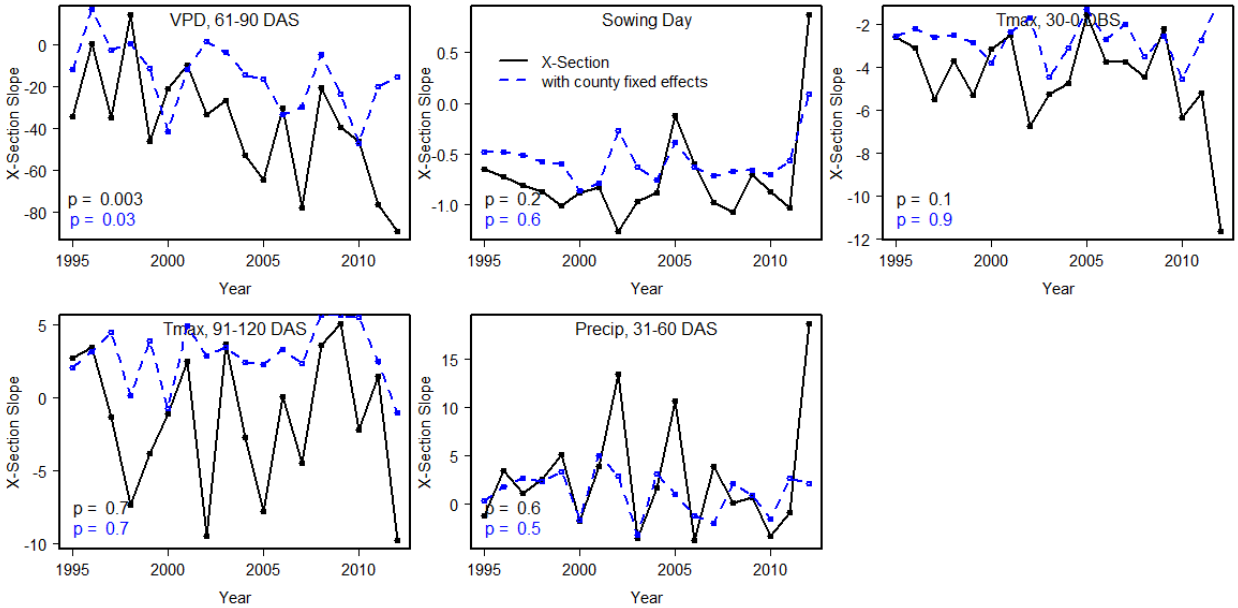

Fig. S7

Coefficients for a cross-sectional regression between maize yields and different predictors in each year of the study period. Solid black indicates simple regression of yield vs. W, where W is the respective weather variable. Dashed blue lines indicate result from a regression that also includes county fixed-effects, thus relying only on deviations from county means. P-values indicate significance of trends over time, with $p < 0.05$ deemed significant. Note that yields appear to be increasingly sensitive to VPD over time (top left panel).

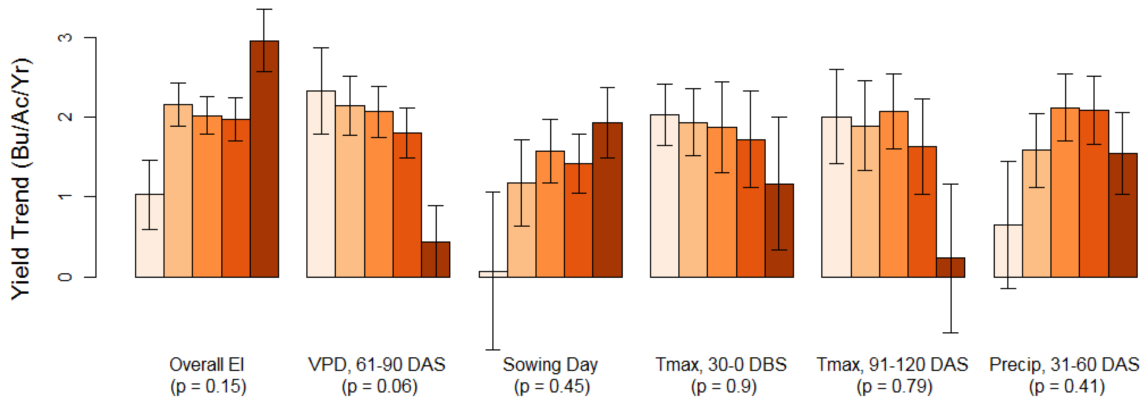

Fig. S8

Same as Fig. S5a but using a dataset spanning a wider group of Corn Belt states: Illinois, Indiana, Iowa, Ohio, Minnesota, Wisconsin. P values refer to time trend of difference between highest and lowest quintile, with $p<0.05$ deemed significant.

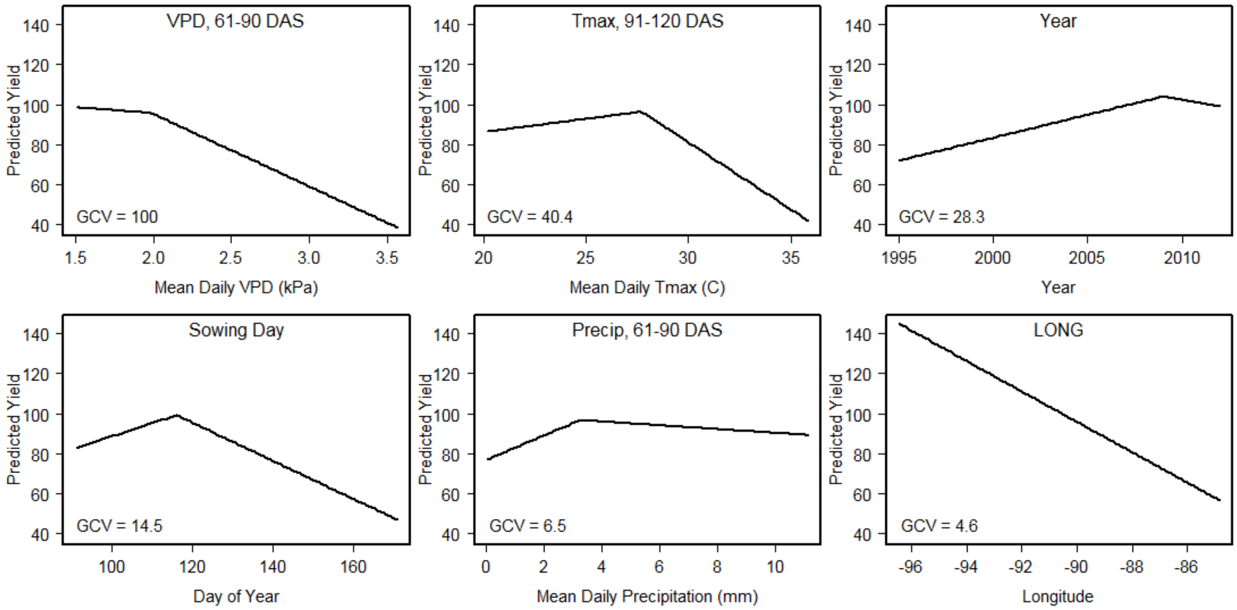

Fig. S9

Summary of the response curves of the MARS model fit to the maize data for Kansas, Nebraska, and South Dakota (i.e., same as Fig. 2 in main paper but using a dataset for the Western Corn Belt states). See Fig. 2 in main paper for description of response curves.

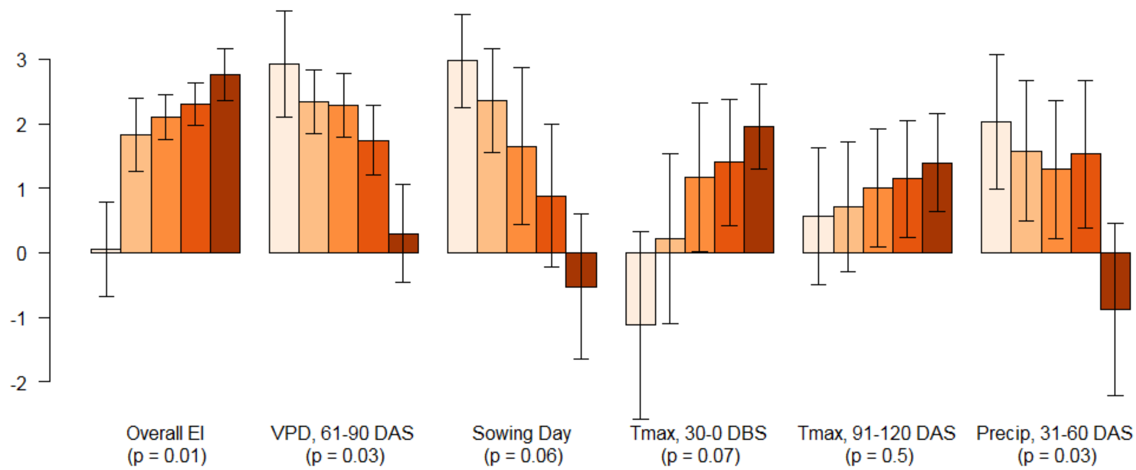

Fig. S10

Same as Fig. S5a but using a dataset for the Western Corn Belt states: Kansas, Nebraska, and South Dakota. Maize yield trends by quintile of EI and each component of EI. P values refer to time trend of difference between highest and lowest quintile, with $p<0.05$ deemed significant.

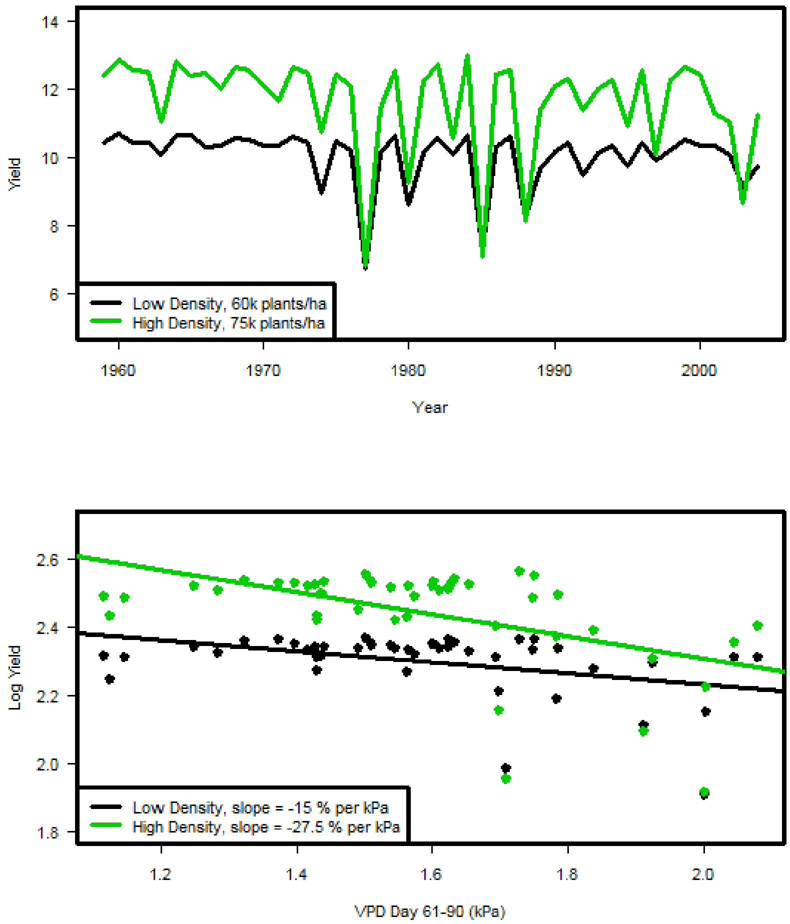

Fig. S11

(Top) APSIM simulations of maize yields for Johnston, Iowa for two different sowing densities, corresponding to the average sowing densities for the region in 1995 and 2012, respectively. Simulations were done for 1959-2005 following ref. (15). (Bottom) Scatter plots of the log of simulated yields vs. VPD for 61-90 days after sowing for the two sowing densities. Simulated sensitivity to VPD nearly doubles for the observed increase sowing density over the study period, similar to the empirical estimates (see Fig. 5 of main paper).

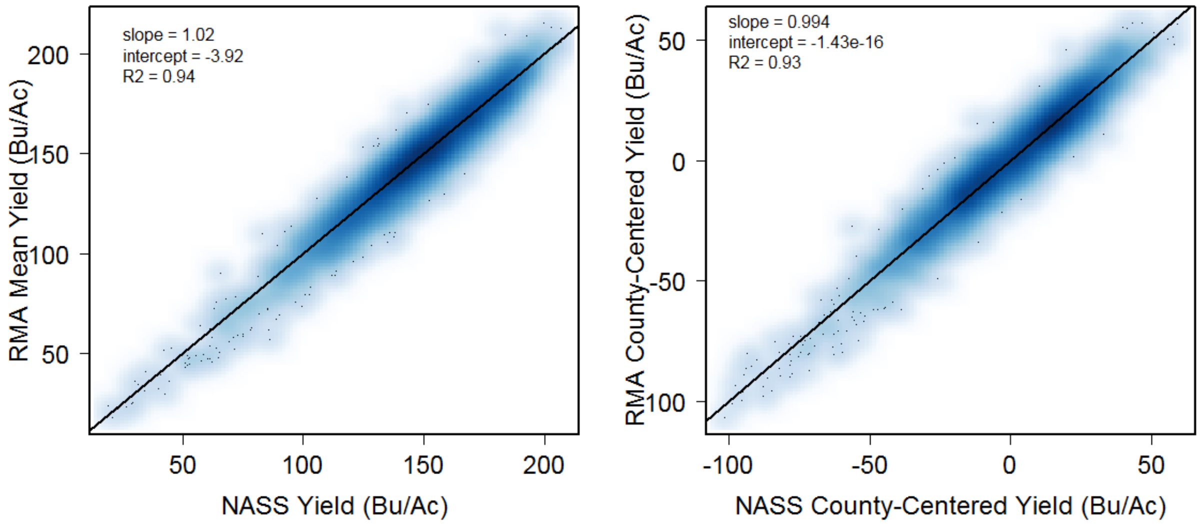

Fig. S12

Comparison of USDA official maize yields for each county (x-axis) with means of RMA reported yield data for fields used in this study for corresponding county (y-axis). Left panel shows raw yields for all study years, and right panel shows yield deviations from county average over the study period.

References

1. H. Campos, M. Cooper, J. E. Habben, G. O. Edmeades, J. R. Schussler, Improving drought tolerance in maize: A view from industry. *Field Crops Res.* **90**, 19–34 (2004). doi:10.1016/j.fcr.2004.07.003

2. C. M. Löffler, J. Wei, T. Fast, J. Gogerty, S. Langton, M. Bergman, B. Merrill, M. Cooper, Classification of maize environments using crop simulation and geographic information systems. *Crop Sci.* **45**, 1708 (2005). doi:10.2135/cropsci2004.0370

3. K. Chenu, R. Deihimfard, S. C. Chapman, Large-scale characterization of drought pattern: A continent-wide modelling approach applied to the Australian wheatbelt—spatial and temporal trends. *New Phytol.* **198**, 801–820 (2013). doi:10.1111/nph.12192 Medline

4. F. Tardieu, Any trait or trait-related allele can confer drought tolerance: Just design the right drought scenario. *J. Exp. Bot.* **63**, 25–31 (2012). doi:10.1093/jxb/err269 Medline

5. Food and Agriculture Organization of the United Nations (FAO), FAO Statistical Databases (2013); http://faostat.fao.org

6. J. McGrath, D. B. Lobell, An independent method of deriving the carbon dioxide fertilization effect in dry conditions using historical yield data from wet and dry years. *Glob. Change Biol.* **17**, 2689–2696 (2011). doi:10.1111/j.1365-2486.2011.02406.x

7. R. J. Donohue, M. L. Roderick, T. R. McVicar, G. D. Farquhar, Impact of CO_2 fertilization on maximum foliage cover across the globe's warm, arid environments. *Geophys. Res. Lett.* **40**, 3031–3035 (2013). doi:10.1002/grl.50563

8. D. N. Duvick, The contribution of breeding to yield advances in maize (*Zea mays* L.). *Adv. Agron.* **86**, 83–145 (2005). doi:10.1016/S0065-2113(05)86002-X

9. M. Tollenaar, J. Wu, Yield improvement in temperate maize is attributable to greater stress tolerance. *Crop Sci.* **39**, 1597 (1999). doi:10.2135/cropsci1999.3961597x

10. G. Hammer, Z. Dong, G. McLean, A. Doherty, C. Messina, J. Schussler, C. Zinselmeier, S. Paszkiewicz, M. Cooper, Can changes in canopy and/or root system architecture explain historical maize yield trends in the U.S. corn belt? *Crop Sci.* **49**, 299 (2009). doi:10.2135/cropsci2008.03.0152

11. NRC, *The Impact of Genetically Engineered Crops on Farm Sustainability in the United States* (National Research Council, Washington, DC, 2010).

12. D. J. Lyon, G. L. Hammer, G. B. McLean, J. M. Blumenthal, Simulation supplements field studies to determine no-till dryland corn population recommendations for semiarid western Nebraska. *Agron. J.* **95**, 884 (2003). doi:10.2134/agronj2003.0884

13. M. Tollenaar, E. Lee, Yield potential, yield stability and stress tolerance in maize. *Field Crops Res.* **75**, 161–169 (2002). doi:10.1016/S0378-4290(02)00024-2

14. M. Bänziger, P. S. Setimela, D. Hodson, B. Vivek, Breeding for improved abiotic stress tolerance in maize adapted to southern Africa. *Agric. Water Manage.* **80**, 212–224 (2006). doi:10.1016/j.agwat.2005.07.014

15. J. H. Friedman, Multivariate adaptive regression splines. *Ann. Stat.* **19**, 1–67 (1991). doi:10.1214/aos/1176347963

16. Materials and methods are available as supplementary materials on *Science* Online.

17. D. B. Lobell, G. L. Hammer, G. McLean, C. Messina, M. J. Roberts, W. Schlenker, The critical role of extreme heat for maize production in the United States. *Nat. Clim. Change* **3**, 497–501 (2013). doi:10.1038/nclimate1832

18. J. D. Ray, R. W. Gesch, T. R. Sinclair, L. Hartwell Allen, The effect of vapor pressure deficit on maize transpiration response to a drying soil. *Plant Soil* **239**, 113–121 (2002). doi:10.1023/A:1014947422468

19. B. Barnabás, K. Jäger, A. Fehér, The effect of drought and heat stress on reproductive processes in cereals. *Plant Cell Environ.* **31**, 11–38 (2008). Medline

20. A. E. Fonseca, M. E. Westgate, Relationship between desiccation and viability of maize pollen. *Field Crops Res.* **94**, 114–125 (2005). doi:10.1016/j.fcr.2004.12.001

21. P. Woli, J. W. Jones, K. T. Ingram, C. W. Fraisse, Agricultural Reference Index for Drought (ARID). *Agron. J.* **104**, 287 (2012). doi:10.2134/agronj2011.0286

22. C. D. Messina, D. Podlich, Z. Dong, M. Samples, M. Cooper, Yield-trait performance landscapes: From theory to application in breeding maize for drought tolerance. *J. Exp. Bot.* **62**, 855–868 (2011). doi:10.1093/jxb/erq329 Medline

23. National Agriculture Statistics Service, Corn Objective Yield Survey Data, 1992-2006 (NASS, U.S. Department of Agriculture, Washington, DC, 2007); http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1749

24. National Agriculture Statistics Service, Soybean Objective Yield Survey Data, 1992-2006 (NASS, U.S. Department of Agriculture, Washington, DC, 2007); http://usda01.library.cornell.edu/usda/current/SoyObjYield/SoyObjYield-07-27-2007.pdf

25. National Agriculture Statistics Service, 2013 Illinois Annual Statistics Bulletin (NASS, U.S. Department of Agriculture, Washington, DC, 2013); http://www.nass.usda.gov/Statistics_by_State/Illinois/Publications/Annual_Statistical_Bulletin/2013/toc.html#fieldcrops

26. D. J. Connor, R. S. Loomis, K. G. Cassman, *Crop Ecology: Productivity and Management in Agricultural Systems* (Cambridge Univ. Press, 2011).

27. M. J. Roberts, W. Schlenker, in *The Economics of Climate Change: Adaptations Past and Present*, G. D. Libecap, R. H. Steckel, Eds. (Univ. of Chicago Press, Chicago, 2011); pp. 225–251.

28. N. Wells, S. Goddard, M. J. Hayes, A self-calibrating Palmer Drought Severity Index. *J. Clim.* **17**, 2335–2351 (2004). doi:10.1175/1520-0442(2004)017<2335:ASPDSI>2.0.CO;2

29. J. Peixoto, A. H. Oort, The climatology of relative humidity in the atmosphere. *J. Clim.* **9**, 3443–3463 (1996). doi:10.1175/1520-0442(1996)009<3443:TCORHI>2.0.CO;2