Future warming increases probability of globally synchronized maize production shocks

Michelle Tigchelaar[a,1], David S. Battisti[a], Rosamond L. Naylor[b], and Deepak K. Ray[c]

[a]Department of Atmospheric Sciences, University of Washington, Seattle, WA 98195; [b]Center on Food Security and the Environment, Stanford University, Stanford, CA 94305; and [c]Institute on the Environment, University of Minnesota, St. Paul, MN 55108

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Meeting the global food demand of roughly 10 billion people by the middle of the 21st century will become increasingly challenging as the Earth's climate continues to warm. Earlier studies suggest that once the optimum growing temperature is exceeded, mean crop yields decline and the variability of yield increases even if interannual climate variability remains unchanged. Here, we use global datasets of maize production and climate variability combined with future temperature projections to quantify how yield variability will change in the world's major maize-producing and -exporting countries under 2 °C and 4 °C of global warming. We find that as the global mean temperature increases, absent changes in temperature variability or breeding gains in heat tolerance, the coefficient of variation (CV) of maize yields increases almost everywhere to values much larger than present-day values. This higher CV is due both to an increase in the SD of yields and a decrease in mean yields. For the top four maize-exporting countries, which account for 87% of global maize exports, the probability that they have simultaneous production losses greater than 10% in any given year is presently virtually zero, but it increases to 7% under 2 °C warming and 86% under 4 °C warming. Our results portend rising instability in global grain trade and international grain prices, affecting especially the ∼800 million people living in extreme poverty who are most vulnerable to food price spikes. They also underscore the urgency of investments in breeding for heat tolerance.

climate change | food security | price volatility

Global cereal markets have been highly volatile during the past decade, and this pattern of volatility is likely to persist well into the future. Between 2007 and 2017, nominal prices for maize, wheat, and rice varied widely, with peak monthly prices 200–300% higher than low monthly prices (1). Such volatility creates great uncertainty for cereal farmers, livestock producers, and the agribusiness sector, and it reduces food access for poor consumers when production falls and prices spike. While there are many factors contributing to the recent pattern of cereal market volatility [e.g., biofuel policies, trade policies, grain stocking policies, fluctuating international financial conditions (2, 3)], climate-induced production shocks have played a significant role. Here, we build on existing literature quantifying the impact of climate change on crop yields over the course of the 21st century and examine how the rising mean global temperature is likely to increase crop yield variability worldwide.

Numerous studies have concluded that unabated warming will lead to substantial declines in mean crop yields by the mid-21st century, and that the most serious agricultural impacts will occur in the tropics, where the majority of the world's food-insecure population resides (4–8). High temperatures negatively impact plant development in multiple ways, including reduced spikelet fertility, reduced grain filling, and increased respiration (9, 10). Generally, crops have an optimal temperature for performance, beyond which yields rapidly decline (11, 12) (Fig. 1). With continued warming under business-as-usual greenhouse gas emissions, global crop yields are expected to decline significantly: For every degree increase in global mean temperature, yields are projected to decrease, on average, by 7.4% for maize, 6.0% for wheat, 3.2% for rice, and 3.1% for soybean (5). Although rainfall variability and resulting changes in soil moisture also affect crop yields, the negative effects of future warming are expected to outweigh those of precipitation changes due to the large magnitude of projected warming compared with historical variability (13).

An increase in the mean temperature beyond the optimum growing temperature also results in greater yield variability, even if interannual temperature variability remains the same (Fig. 1). Regional studies of climate change impacts on staple crops, such as maize in the United States (14–16) and wheat (17), maize (18), and rice (19) in China, project that an increase in mean temperature will lead to rising yield variability and incidences of crop failure (4). Our study extends these regional analyses to the global scale by aggregating climate impacts on yield variability across the world's largest producing and exporting countries. Specifically, we quantify the likelihood of multiple large-producing and -exporting countries facing simultaneous crop shortfalls in the future, with implications for global cereal trade, prices, and food security. Our analysis focuses on maize production, as maize is the world's most grown and heavily traded cereal crop in international markets, and the relationship between maize yields and climate is fairly well established.

Changes in Mean Yields

Present-day maize yields vary widely across the globe, depending on the regional climate and crop management system. Yields are highest in intensive, temperate-zone production systems, such as the US Corn Belt and western Europe, followed by regions in

Significance

Climate-induced shocks in grain production are a major contributor to global market volatility, which creates uncertainty for cereal farmers and agribusiness and reduces food access for poor consumers when production falls and prices spike. Our study, by combining empirical models of maize production with future warming scenarios, shows that in a warmer climate, maize yields will decrease and become more variable. Because just a few countries dominate global maize production and trade, simultaneous production shocks in these countries can have tremendous impacts on global markets. We show that such synchronous shocks are rare now but will become much more likely if the climate continues to warm. Our results underscore the need for continued investments in breeding for heat tolerance.

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Data deposition: Yield projections can be downloaded from https://mtigchelaar.github.io/maize-variability/.

[1]To whom correspondence should be addressed. Email: tigchelaar@atmos.uw.edu.

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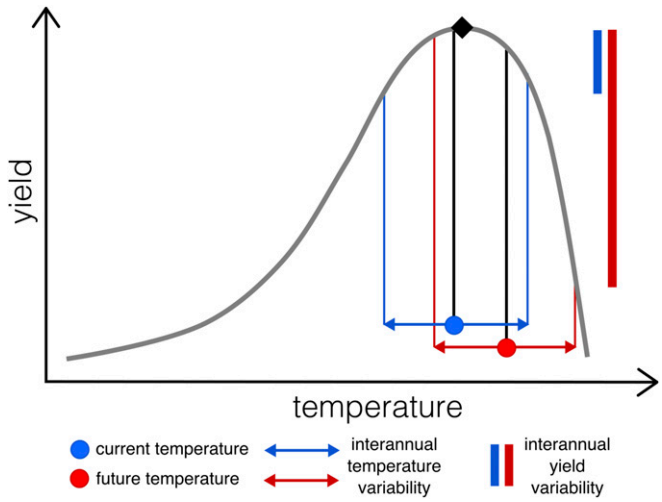

Fig. 1. Schematic representation of temperature-yield relationship. In the absence of breeding for heat tolerance, an increase in mean temperature beyond the optimum temperature (♦) will lead to a decrease in mean yield and an increase in yield variability, assuming interannual temperature variability stays the same.

China, Argentina, and South Africa. Maize research and development organizations, such as the International Maize and Wheat Improvement Center and the Australian Center for International Agricultural Research (ACIAR), have previously used the different growing conditions of maize to define so-called "maize mega-environments" across which maize cultivars perform similarly (20, 21). The response of maize yields to climate variability and climate change will differ between these different environments and will also depend on management characteristics, such as cropping intensity and irrigation. We therefore use climate (growing season mean temperature, growing season total precipitation, and latitude) and cropping (mean yield and level of irrigation) data as input for a K-means cluster analysis in which we divide the globe into seven growing regions that correspond closely to the maize mega-environments (*SI Appendix*, Figs. S1 and S2). For each of these seven regions, we develop statistical models relating changes in yield to climate variability (*Materials and Methods*).

Empirical models of climate-crop relationships use a variety of indicators to capture the effects of climate variability on crop yields (10). Growing season mean temperature and precipitation are easily calculated and commonly used metrics. However, these season-mean variables smooth out the opposing contributions of early season warming and extreme summer heat on plant development. Alternative model formulations therefore make use of growing and killing degree days (GDDs and KDDs, respectively) to distinguish between thermal time to development and the harmful effects of high temperatures (11, 12). Using temperatures of individual months rather than temperatures averaged over the growing season is another way to capture the differential effect of temperatures on plant development by phenological phase. For each growing region, we test a number of model formulations and select the one providing the best fit (*Materials and Methods*). In six of seven clusters, this is a model using a degree day formulation. The estimated model coefficients (*SI Appendix*, Table S8) are consistent with well-understood biological constraints (*SI Appendix*).

In all but the most draconian emission reduction scenario, global annual mean temperature rises by about 2 °C by the mid-21st century compared with the 1980–1999 average. We evaluate the effect of this common temperature target on crop yields by normalizing the monthly multimodel mean patterns of end-of-century temperature changes from the Coupled Model Intercomparison Project Phase 5 (CMIP5) Representative Concentration Pathway 8.5 (RCP8.5) simulations by the global annual mean temperature and adding the temperature anomaly pattern to present-day temperature fields (*Materials and Methods* and *SI Appendix*, Fig. S4). We thus create a future climate history that features identical variability as in the historical record but acting on top of an annual cycle in temperature associated with global annual mean warming of 2 °C. Additionally, we assess the risk of failing to reduce carbon emissions by quantifying the potential impacts of 4 °C global annual mean warming (*SI Appendix*, Fig. S4). Under business-as-usual emissions (RCP8.5), the global mean temperature is projected to increase by 2 °C as early as 2042, with a median prediction of 2055, and by 4 °C between 2075 and 2132. Even in an emissions scenario aiming to stabilize greenhouse gas concentrations by the mid-21st century (RCP4.5), global mean temperature could rise by 2 °C as early as 2052 (*SI Appendix*, Table S1). We do not consider the effect of changes in the annual cycle of rainfall on future crop yields because of the high uncertainties in the magnitude and pattern of future precipitation changes, and the comparatively higher signal-to-noise ratio in temperature changes (13).

With the exception of a few locations in western Europe and China, maize yields decline everywhere in response to 2 °C of warming, with particularly strong declines in the southeastern United States, eastern Europe, and southeastern Africa (Fig. 2). In the midlatitudes, an increase in GDDs contributes positively to crop yields, while more KDDs lead to yield declines. At 4 °C warming, the negative contribution of additional KDDs far outweighs the positive effect of increased GDDs, so that substantial changes in mean maize yields of >40% are predicted in many places, most notably in the United States, Mexico, eastern Europe, and southern Africa. These values are within the range of response to warming found in previous empirical and crop modeling studies (5). The magnitude of projected yield changes is comparable between the three linear regression models that we test (*SI Appendix*, Fig. S5). When including quadratic terms in the models, the model fit is generally equivalent or slightly better, and the projected yield reductions are even greater than those projected using the linear models, especially for the 4 °C warming scenario (*SI Appendix*, Fig. S5). The same is true when we use yield ratios as the dependent variable rather than absolute yield anomalies. Our predictions may therefore be on the conservative side.

Global maize production is highly concentrated within a few locations: Just four countries (United States, China, Brazil, and Argentina) produce 68% of the world's maize, and the top four maize-exporting countries combined (United States, Brazil, Argentina, and Ukraine) account for 87% of global maize exports (22) (*SI Appendix*, Table S2). In the United States, China, Brazil, and Argentina (the top four producing countries), mean total production is projected to decline by 18% (17.4–18.3), 10% (10.1–10.7), 8% (7.6–8.1), and 12% (11.3–11.9), respectively, under 2 °C of global warming and by 46% (45.4–47.5), 27% (26.7–28.0), 19% (19.0–19.9), and 29% (27.9–29.0) with 4 °C of warming (mean and 90% confidence intervals; *SI Appendix*, Table S6). Averaged over the 2012–2017 period, global annual

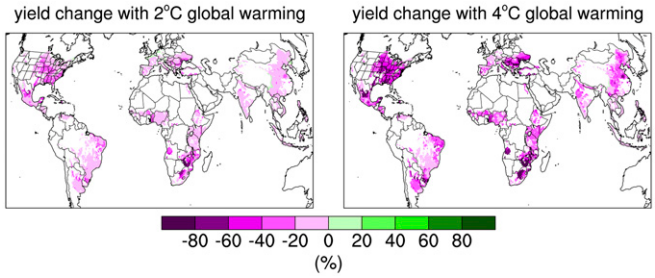

Fig. 2. Warming-induced changes in mean yield. Relative change in average yield (%) following annual mean global warming of 2 °C (*Left*) and 4 °C (*Right*).

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maize exports were 125 million tons and global maize production was 986 million tons (22). In response to 2 °C of global warming, total production in the top four maize-exporting countries is projected to decline by 53 million tons (51.9–54.8), equivalent to 43% (41.5–43.8) of global maize export volume. For 4 °C of warming, projected production declines in these top-exporting countries increase to 139 million tons (135.5–142.0), which amounts to 14% (13.7–14.4) of current global production and exceeds present-day exports.

Changes in Yield Variability

Not all variability in yields is a result of variability in weather and climate. Socioeconomic drivers, plant breeding, pests and pathogens, and other agronomic variables also contribute to yield and production variance. In highly managed, high-yield cropping systems, such as those in the United States, Europe, and China, climate variability accounts for a relatively large share of the total yield variance compared with low-yield environments (Fig. 3 *A* and *B* and *SI Appendix*, Table S3). Irrigation generally reduces sensitivity to changes in temperature (23), lowering the climate-driven share of yield variability in intensive, highly managed environments (*SI Appendix*, Table S3). In this study, we do not consider future changes in precipitation and, as such, do not quantify changes in future yield variance that result from the covariance between temperature and rainfall variability. Depending on the growing region, the covariance between temperature and precipitation currently explains, on average, 2% of the total yield variance and 17% of the climate-driven variance.

A commonly used measure of yield variability is the coefficient of variation (CV) (24), which captures both changes in the SD and mean. In our yield projections, climate warming causes the CV to increase in most places, especially in the United States, eastern Europe, and southern Africa (Fig. 3 *C* and *D*), to values many fold higher than present-day values (Fig. 3 *A* and *B*). A decomposition of CV changes into contributions from changes in the mean and SD (*SI Appendix*, Fig. S6) shows that both factors contribute to this increase: Not only will mean maize yields decrease with warming (Fig. 2), leading to an increase in CV, but absolute variability is also projected to increase, including in the major maize-producing regions of the United States, Europe, China, and Argentina (*SI Appendix*, Fig. S6). The increase in CV due to increased yield variability is comparable to or greater than the increase due to decreasing mean yields. In locations where crop failures become the norm under high (4 °C) warming (mostly in tropical, low-yield environments), the SD of yields ultimately decreases.

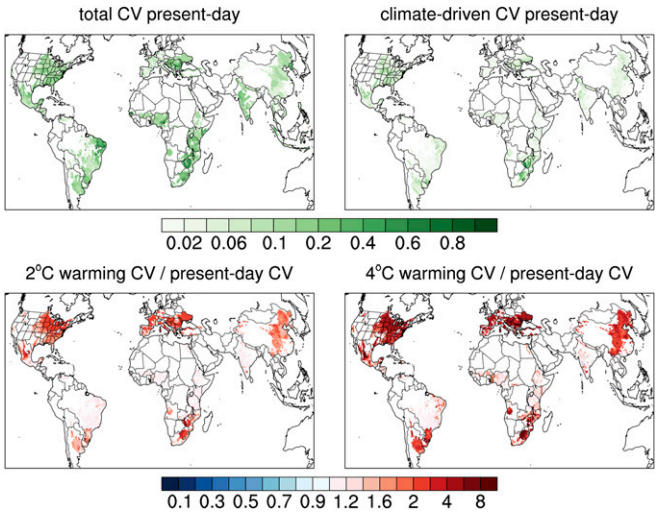

Fig. 3. Warming-induced changes in yield variability. (*Top*) Present-day CV due to all sources of variability (*Left*) and climate variability (*Right*). (*Bottom*) Ratio of changes in climate-driven CV following annual mean global warming of 2 °C (*Left*) and 4 °C (*Right*).

An increase in yield variability has implications both for farmers, who rely on their crops for income stability, and for global markets, where crop availability influences food prices (2, 16, 25). Six countries, the United States, China, Brazil, Argentina, Ukraine, and France, collectively account for 73% of global production and 93% of total exports, and in all of these countries, mean yields decrease and yield variability increases under higher temperatures compared with present-day values (Fig. 4 and *SI Appendix*, Figs. S7 and S9 and Table S7). In line with the theoretical prediction that yield losses will decline precipitously above an optimum temperature (Fig. 1), our results show that extreme yield losses become increasingly likely under global warming. For Ukraine, in particular, yield losses of up to 100% become a possibility under 4 °C warming, where the losses are compared with the mean yield baseline for the period 1999–2008 (*Materials and Methods*).

Extreme crop losses in large-producing areas are presently rare because of the highly controlled environments in which maize is grown in these regions. Yields are tightly constrained around their mean (Fig. 4), and climate-induced yield losses of >10% only occur every 15 to 100 y (Table 1). Climate-induced yield losses of >20% are virtually unseen. In a warming climate, however, these extreme crop failures become increasingly likely. With a 2 °C warming, the probability of a >10% yield loss in any given year in the world's top four producing countries (United States, China, Brazil, and Argentina) rises to 69%, 46%, 39%, and 50%, respectively. Assuming that weather varies independently between our regional clusters, the probability that maize production will fall by more than 10% in the high-productivity areas of all four countries in the same year is 0% today but increases to 6% under 2 °C warming and 87% under 4 °C warming. Given that these four countries alone account for almost 70% of global maize production, such synchronized production shocks are likely to have tremendous impacts on global cereal markets. This pattern is even more pronounced for the top four exporting countries (United States, Brazil, Argentina, and Ukraine). With a 2 °C warming, the probability of a >10% yield loss in any given year for each of these four countries is 69%, 39%, 50%, and 52%, respectively. Collectively, the probability that these large-exporting countries will incur simultaneous production losses greater than 10% in any given year is virtually zero under present-day climate conditions but rises to 7% under 2 °C warming and 86% under 4 °C warming. The projected changes in variability are robust to statistical uncertainty in model coefficients (*SI Appendix*, Fig. S9 and Table S7).

Implications for Food Security

The projected increase in maize yield variability across major producing and exporting countries has important implications for global food security, as defined by the ability to provide adequate and affordable food supplies to all people at all times and to ensure economic access to a nutritious diet for all. Meeting this food security goal will become increasingly difficult as the world's population grows from 7.5 billion today to ∼10 billion by 2050, a 30% increase (26). Virtually all of this growth will occur in developing countries, most notably within sub-Saharan Africa, and over half the global population will reside in urban areas, where international trade plays a key role in ensuring affordable food supplies.

Temperature-induced volatility in global maize prices results from production shocks in both exporting and importing countries. When rising temperatures affect yields in large maize-exporting countries, such as the United States, Brazil, Argentina, and Ukraine, global export supply falls. Similarly, when shocks affect large maize-producing countries that also import, such as China and Mexico, global import demand rises. Synchronous production shocks across multiple large trading countries is therefore expected to lead to a higher frequency in international price spikes. Our analysis indicates that the probability of a synchronous decline in yield of >10% for the world's three largest maize exporters and three largest maize importers is

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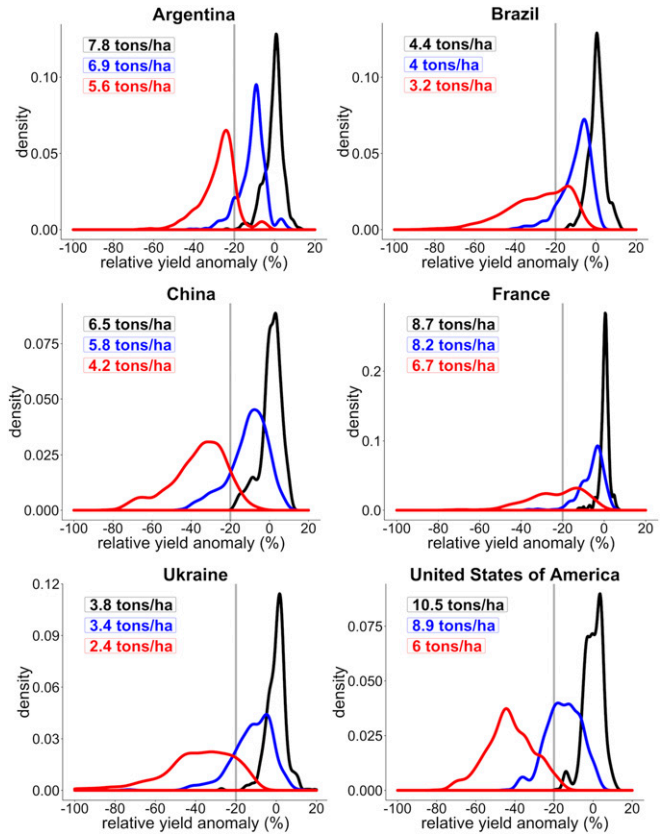

Fig. 4. Warming-induced changes in yield variability in top-producing regions of the six largest maize-producing and -exporting countries (*SI Appendix*, Table S2): Probability density functions of yield anomalies with respect to present-day mean yield for present-day climate (black), following 2 °C of annual mean global warming (blue), and following 4 °C of annual mean global warming (red). The vertical gray line denotes a relative yield reduction of 20%, and boxed values indicate mean present-day yield in these areas for present-day climate (1999–2008; black) and for 2 °C (blue) and 4 °C (red) warming.

virtually zero today but jumps to 69% under 4 °C warming (Table 1). Simultaneous production shocks among these large trading countries will have a direct impact on urban consumers, as well as on agribusiness, grain producers, and poor households that spend a large share of their income on staple foods. The degree to which these groups in any given country is affected by international market volatility depends importantly on trade policies designed to insulate domestic markets from international price fluctuations. From a global dataset of 82 countries for the period 1985–2010, the price transmission coefficient for maize is estimated to be 0.63 (27), meaning that, on average, domestic markets experience about two-thirds of the price volatility seen in international markets.

Recent experience from the 2006–2008 global food crisis suggests that if food prices spike and urban consumers become discontent, governments become vulnerable to collapse, particularly in developing countries where consumer food safety nets (e.g., the US Supplemental Nutrition Assistance Program) do not exist (2). As a result, many governments restrict cereal trade to stabilize domestic food markets, resulting in even greater international market instability (27–29). During the 2006–2008 crisis, large maize-exporting countries, including Brazil, Argentina, and Ukraine, imposed export bans on maize, and thus further reduced global export supply, while maize-importing countries introduced trade incentives to lower the price of imported grain, and thus raised import demand. Together, these policies accounted for about one-ninth of the 83% increase in the international maize price over the short period (29). Similar trade policies were implemented for rice and wheat, with even greater contributions to international price spikes (27–29).

The combination of global crop yield variability and disruptive government trade intervention in staple grain markets suggests that the pattern of high price volatility experienced over the past decade (*SI Appendix*, Fig. S8) will likely persist, or even intensify in the future, with rising temperatures. Maize is an important crop to examine in this context, as it accounts for roughly one-third of both global cereal production and trade, and it is closely connected to other cereal and oil crops through its versatile role in food, animal feed, and fuel markets (30). Grain and oil crop prices are highly correlated over time as a result of substitutions in consumption and production (*SI Appendix*, Table S5). The impact of rising mean temperatures on maize yields and maize yield variability thus has far-reaching consequences for the stability of global food systems overall as well as for global food security.

Conclusion

Our work suggests that global cereal yields and markets will become increasingly variable throughout the 21st century, even if temperature variability remains the same. In our analysis, we assume constant technology and management in global maize systems, which is abstracted from real-world adaptations and investments in agriculture. In low-productivity maize regions where substantial yield gaps remain, closing those gaps would offset some of the projected yield losses shown in our study. However, most of the world's maize volume is currently grown in highly intensified, high-productivity agricultural systems, such as the United States and China, where the gap between yield and potential yield is narrow (31). For these regions, the two ways to avoid a low-yield, high-volatility future while retaining maize systems are to mitigate CO_2 emissions aggressively or to breed for improvements in heat tolerance: in effect, breeding to stay on the temperature for optimum yield (Fig. 1) in the face of a rapidly warming climate. Indeed, breeders are well aware of the importance of heat stress for yield. Unfortunately, the mechanisms for heat tolerance in maize (and other major grains) are

Table 1. Probability that in any given year, the relative yield in a country's most productive region (*Materials and Methods*) will decline by 10% or 20% of the present-day mean yield for the 10 top-producing countries individually and combinations of the countries that produce or trade the most maize

	Present-day climate, %		2 °C warming, %		4 °C warming, %	
Country	>10	>20	>10	>20	>10%	>20
United States	3.8	0.0	68.6	29.5	100.0	96.9
China	6.6	0.0	46.2	16.8	98.8	89.2
Brazil	1.4	0.0	38.7	9.4	90.5	64.1
Argentina	3.4	0.1	50.0	9.9	96.9	86.9
Ukraine	2.5	0.3	51.8	19.2	98.2	85.0
Mexico	1.0	0.0	18.5	1.7	79.6	44.0
India	0.8	0.0	7.4	1.6	50.9	10.4
France	0.9	0.0	21.1	2.3	81.7	52.3
Canada	0.3	0.0	12.0	1.1	70.0	40.6
South Africa	16.6	6.9	79.2	59.8	97.5	94.5
Top four producing*	0.0	0.0	6.1	0.0	86.6	48.1
Top four exporting†	0.0	0.0	6.9	0.1	86.1	45.8
Top export + import‡	0.0	0.0	1.1	0.0	68.9	21.2

The magnitude and share of production and trade for the top-producing maize countries are shown in *SI Appendix*, Table S2.
*United States, China, Brazil, Argentina.
†United States, Brazil, Argentina, Ukraine.
‡United States, China, Brazil, Argentina, Mexico.

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extremely complex and poorly understood, and progress in this area has been modest despite the innovation of techniques to accelerate breeding (32–35). The development of heat-tolerant varieties will likely require advanced genetic techniques, including genetic modification, which raises issues of social acceptance. Without significant genetic advances in heat tolerance, however, and the successful dissemination of heat-tolerant varieties throughout these high-productivity systems, there may be little opportunity to increase maize production and stabilize grain markets in the face of projected yield declines. Breeding for heat tolerance is thus a high-priority, but an as-of-yet unattained, goal in maize development (7).

Materials and Methods

Datasets.

Crop data. We obtained annual maize yield and harvested area data from a global gridded dataset at 0.5° resolution that synthesizes ∼2.5 million census observations and spans the period 1961–2008 (31, 36–38). Plant and harvest dates of maize were derived from a global gridded dataset at 0.5° resolution, which represents average planting conditions in roughly the year 2000 (39). The Monthly Irrigated and Rainfed Crop Areas around the year 2000 (MIRCA2000) dataset contains monthly growing areas and annual harvested areas for 26 different crops at 0.5° resolution (40). We calculate percent irrigated area by dividing the irrigated area in each grid cell by the total harvested area in that cell. Data on country-level production of individual crops and total agricultural output of each country were obtained from the Food and Agriculture Organization Corporate Statistical Database (1). Based on these data, we excluded grid cells if their harvested area was less than 1% of the grid cell area, if a country's maize production was not at least 5% of its total agricultural production or greater than 3 million tons in total, or if yield data appeared to be erroneous (>17 tons per hectare).

Climate data. Monthly temperature and precipitation data derive from the Climatic Research Unit Time-Series Version 3.23 dataset, which presents data from the period 1901–2014 on a 0.5° global grid (41). Daily mean, minimum, and maximum temperatures are obtained from the European Centre for Medium-Range Weather Forecast ReAnalysis Interim (ERA-Interim) dataset (42), which is available from 1979 to 2015. Mean temperature at 2-m height is output four times daily, so daily mean is calculated as the mean over those four daily values. Minimum (maximum) temperatures at 2-m height are output eight times daily as the minimum (maximum) over the preceding 3 h, so the daily minimum, $T_{\min,d}$, (maximum, $T_{\max,d}$) is calculated by finding the minimum (maximum) over those eight time steps. The ERA-Interim data are available on a 0.75° resolution grid and are interpolated using bilinear interpolation to the 0.5° resolution grid on which the crop and monthly climate data are available. For the temperature threshold years in *SI Appendix*, Table S1, global annual mean temperature projections for all CMIP5 models in three emission scenarios (RCP4.5, RCP6.0, and RCP8.5) were pulled from the Royal Netherlands Meteorological Institute (KNMI) Climate Explorer (43).

We develop several empirical crop models (below) that incorporate various climate indices. Growing season means (temperature, T_{seas}) and sums (precipitation, P_{seas}) are calculated by linearly interpolating the monthly mean temperature and precipitation data over 365 d and taking the average over the days between plant and harvest dates (39). For the linear regression model that includes the temperature of individual months, the middle 3 mo of the growing season at each location are selected (T_{M1}, T_{M2}, and T_{M3}; 3 mo is the minimum growing season length for maize). GDDs and KDDs are calculated following earlier work (44). GDDs are defined for each day as follows:

$$GDD_d = \frac{T^*_{\min,d} + T^*_{\max,d}}{2} - T_{\text{low}}, \quad [1]$$

where,

$$T^*_{\max,d} = \begin{cases} T_{\max,d} & \text{if } T_{\text{low}} < T_{\max,d} < T_{\text{high}}, \\ T_{\text{low}} & \text{if } T_{\max,d} \le T_{\text{low}}, \\ T_{\text{high}} & \text{if } T_{\max,d} \ge T_{\text{high}}. \end{cases} \quad [2]$$

$T^*_{\min,d}$ is defined analogously. KDDs for each day are defined as follows:

$$KDD_d = \begin{cases} T_{\max,d} - T_{\text{high}} & \text{if } T_{\max,d} > T_{\text{high}}, \\ 0 & \text{if } T_{\max,d} \le T_{\text{high}}. \end{cases} \quad [3]$$

T_{low} is set to 9 °C, and T_{high} is set to 29 °C. Yearly GDDs and KDDs are obtained by summing the daily values (GDD_d and KDD_d) over the growing season.

Future climate projection data were obtained from the CMIP5 database (45) for the business-as-usual scenario of RCP8.5. First, we constructed the canonical global warming temperature pattern (46) for each of the RCP8.5 CMIP5 models by taking the difference in monthly climatology between the 2080–2099 and 1980–1999 time periods, normalized by the global annual mean temperature change. We then take the multimodel mean over these spatial patterns and scale them to get the global warming pattern associated with a 2 °C or 4 °C global warming model. The future climate is then calculated by adding the change in the (2 °C or 4 °C warmer) climatology to the observed (1979–2008) climate history, thus preserving the present-day interannual and daily temperature variability.

Clustering. It is expected that the sensitivity of maize to climate variability is similar within regions of similar mean climate and management characteristics. Based on the definition of maize mega-environments as defined by, for example, the ACIAR (20), the following variables are used as input for a K-means cluster analysis: growing season mean temperature, growing season mean precipitation, percent irrigated area in each grid cell, mean yield, and latitude. For all time-varying quantities, averages over the period 1989–2008 are calculated. Variables are standardized before the clustering. Because there is no objective means of determining the optimal number of clusters, we rather arbitrarily select seven. Results are found to be insensitive to whether 5, 7, or 10 clusters are used (*SI Appendix*, Table S9). A map of the cluster division is shown in *SI Appendix*, Fig. S1, with the corresponding statistics shown in *SI Appendix*, Fig. S2. A description of each of the seven clusters is given in *SI Appendix*, Table S3. There is a close correspondence between the clusters and the commonly defined maize mega-environments (*SI Appendix*).

Linear Models. The regression models are calculated using yield and climate anomalies with respect to a time-changing mean. Because technology-driven trends in maize yields are substantial and nonlinear, we calculate yield anomalies with respect to a time trend by subtracting a third-order polynomial fit through the yield data at each grid cell. Climate anomalies are calculated by removing a linear trend, which is generally small over this period. The results are therefore insensitive to the climate detrending.

The performance of three different empirical crop models is compared:

$$Y'_{t,i} = \beta_{0,c} + \beta_{1,c} T'_{seas\ t,i} + \beta_{2,c} P'_{seas\ t,i} + \epsilon_{t,i},$$

$$Y'_{t,i} = \beta_{0,c} + \beta_{1,c} T'_{M1\ t,i} + \beta_{2,c} T'_{M2\ t,i} + \beta_{3,c} T'_{M3\ t,i} + \beta_{4,c} P'_{seas\ t,i} + \epsilon_{t,i},$$

$$Y'_{t,i} = \beta_{0,c} + \beta_{1,c} GDD'_{t,i} + \beta_{2,c} KDD'_{t,i} + \beta_{3,c} P'_{seas\ t,i} + \epsilon_{t,i},$$

where Y is yield; prime symbols indicate anomalies; β values are the various regression coefficients; ϵ is the residual; and the subscripts t, i, and c indicate year, location, and cluster, respectively. For each cluster, all data points are strung together and the model is fitted to the entire dataset. In each cluster, we select the model that maximizes variance in a 10-fold cross-validation (*SI Appendix*, Table S3). In all but one of the clusters, this is the same model as the model that maximizes the variance explained of the cluster-averaged annual yield anomalies; in six of seven of the clusters, the degree day model performs best. Because yield anomalies are used as the dependent variable, the intercept coefficients β_0 are all zero, within statistical uncertainty. As daily data are only available since 1979, the fitted models span the period 1980–2008. Because of strong trends in maize yields and harvested area over the past three decades, we use mean yield and harvested area over only the last 10 y of the dataset (1999–2008) as the baseline to compare future yields against.

It should be noted that the mean summer temperature with 4 °C of global warming is well outside the present-day range of interannual temperature variability in many locations, and that our statistical models thus have not been tested for these temperature regimes. Similarly, however, this level of warming is also outside the validation range of field experiments and process-based crop models.

Calculating Changes in Mean and Variability. Before applying the regression models to the future climate data, we first check each grid point to see whether the projected change in growing season mean temperature under 2 °C and 4 °C global warming warrants assignment to a different cluster (*SI Appendix*, Fig. S3). The number of grid points that change cluster (or "adapt") in response to the warming is small compared with total number of grid boxes, so that associated adaptation costs (spread out over several decades of gradual warming) can be assumed to be negligible. Future yield anomalies are calculated by applying the best model for each cluster to the

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future climate data. If the projected yield is less than zero, it is set to equal zero. For Fig. 4 and Table 1, relative yield anomalies are calculated compared with the present-day (1999–2008) mean; for *SI Appendix*, Fig. S7, they are compared with the future mean.

Measures of future yield variability represent only the component of yield variability that is due to climate variability. For the density plots in Fig. 4 and *SI Appendix*, Fig. S7, we pick a roughly 5° × 5° area (~100 grid cells) in the highest producing region of the six highest producing countries (Argentina, Brazil, China, France, Ukraine, and United States) and select the 25 highest producing grid boxes.

Factors Not Considered. This study isolates the effects of future temperature change on maize yields, primarily because of the high uncertainty in precipitation projections. In all models and clusters, the linear precipitation term is positive. This means that in locations where drying is projected, future rainfall reductions will amplify the predicted yield losses. Because interannual and daily temperature variability is currently poorly represented in climate models, this study also assumes no changes in temperature variability, thus ignoring a possible additional contributor to yield variability changes (14). It is possible that fertilization from elevated CO_2 levels could offset these yield losses to some extent. However, as a C4 plant, maize benefits less from elevated CO_2 concentrations than C3 plants like rice and wheat, and there is no conclusive evidence that CO_2 fertilization will lead to substantial yield gains in maize, except during periods of drought (47). We have therefore excluded CO_2 fertilization effects from our analysis.

Data Availability. Yield projections can be downloaded from https://mtigchelaar.github.io/maize-variability/.

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