Earth's Future

RESEARCH ARTICLE
10.1029/2018EF000995

Key Points:
- Since the 1980s, climate has become more favorable for maize production in the United States, balancing increased heat and drought impacts elsewhere
- Heat and drought impacts will become common in several regions that rely on maize production, already at the 1.5 degrees Celsius global warming level
- Unprecedented losses are projected to become common in most maize producing regions (including the United States) at 2 degrees Celsius global warming

Supporting Information:
- Supporting Information S1

Correspondence to:
M. Zampieri,
matteo.zampieri@ec.europa.eu

Citation:
Zampieri, M., Ceglar, A., Dentener, F., Dosio, A., Naumann, G., van den Berg, M., & Toreti, A. (2019). When will current climate extremes affecting maize production become the norm?. *Earth's Future*, *7*, 113–122. https://doi.org/10.1029/2018EF000995

Received 19 JUL 2018
Accepted 15 JAN 2019
Accepted article online 29 JAN 2019
Published online 18 FEB 2019

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When Will Current Climate Extremes Affecting Maize Production Become the Norm?

M. Zampieri[1], A. Ceglar[1], F. Dentener[1], A. Dosio[1], G. Naumann[1], M. van den Berg[1], and A. Toreti[1]

[1]European Commission, Joint Research Centre, Ispra, Italy

Abstract We estimate the effects of climate anomalies (heat stress and drought) on annual maize production, variability, and trend from the country level to the global scale using a statistical model. Moderate climate anomalies and extremes are diagnosed with two indicators of heat stress and drought computed over maize growing regions during the most relevant period of maize growth. The calibrated model linearly combines these two indicators into a single Combined Stress Index. The Combined Stress Index explains 50% of the observed global production variability in the period 1980–2010. We apply the model on an ensemble of high-resolution global climate model simulations. Global maize losses, due to extreme climate events with 10-year return times during the period 1980–2010, will become the new normal already at 1.5 °C global warming levels (approximately 2020s). At 2 °C warming (late 2030s), maize areas will be affected by heat stress and drought never experienced before, affecting many major and minor production regions.

Plain Language Summary Global warming is negatively affecting several aspects of ecosystems and societies. This study analyzes the impact of climate on global and regional maize production in the past and in the future. The effects of warmer temperatures and lack of rain on maize production is first analyzed from reported national maize production time series, and these relationships are then projected into the future, using state-of-the-art global climate model simulations. The worse climate events causing the larger maize production losses observed in the past will become normal already at the global warming level of 1.5 °C compared to the preindustrial period. Our findings highlight the importance of Paris Agreement mitigation goals to hold the increase of global temperature well below 2 °C and pursuing efforts to limit increase to 1.5 °C, as well as the need of identifying and adopting efficient adaptation measures.

1. Introduction

Maize became the most important staple crop with a global production amounting to more than 1×10^9 t (10^{12} kg) since 2013 (FAOSTAT, 2017). Currently, maize is predominantly produced in the United States under well-watered conditions (Klopfenstein et al., 2013; Ranum et al., 2014). Maize was originally cultivated in the tropics, where it was and it is still grown under rainfed conditions (see Figure S1). Maize often provides the primary feedstock for human food products and animal feed and it is sometimes used as fuel (Shiferaw et al., 2011).

Ranging between 28 °C and 32 °C, the optimum daytime temperature to grow maize is higher than for the other important grain crops such as wheat and rice (Sánchez et al., 2014). Nevertheless, maize yields are quite sensitive to the effects of climate anomalies related to high daytime temperatures (Lobell et al., 2011; Lobell et al., 2013; Schlenker & Roberts, 2009; Tebaldi & Lobell, 2018; Zhao et al., 2017).

Several mechanisms can explain the impact of high temperature on maize yields. High seasonal temperature anomalies accelerate maize phenological phase transitions reducing yields (Tebaldi & Lobell, 2018). Daily temperatures above 32 °C can induce heat stress reducing maize photosynthetic rate and increases leaf transpiration (Crafts-Brandner & Salvucci, 2002), compromising water use efficiency. Maize is particularly sensitive to heat stress during the anthesis (flowering) stage by reducing the pollen germination (Gourdji et al., 2013). During the grain filling period, high temperatures shorten kernel filling and decrease yield. Since maize is left in the field to dry up before harvesting, it is usually not sensitive to heat stress and drought in the final period of the cropping season (e.g., Ceglar et al., 2018).

Maize yields are also affected by drought (Zipper et al., 2016) and its nonlinear interactions with heat stress (Iizumi & Ramankutty, 2016; Lesk et al., 2016; Matiu et al., 2017) earlier in the growing season. Drought can cause considerable delays in maize female organ development (Barnabas et al., 2008). During the reproductive stage, water shortage can also result in the inhibition of photosynthesis, thus also reducing the nutrient supply to generative organs. In addition, reduced soil moisture availability can further increase the likelihood of heat stress (Lobell et al., 2013; Ray et al., 2002; Zampieri et al., 2009, 2016).

Under climate change conditions, CO_2 fertilization effects on maize growth should also be taken into account. Despite high uncertainties, most experimental and modeling results point to limited CO_2 effects for the C4 crop maize, compared to the other main C3 crops such as wheat and rice (Bassu et al., 2014; Deryng et al., 2014; Kimball, 2016; Makowski et al., 2015; Schleussner et al., 2018; Semenov & Shewry, 2008). Higher CO_2 concentrations potentially increase maize water use efficiency and may alleviate the effects of drought on maize yields (Crafts-Brandner & Salvucci, 2002). However, the reduced evapotranspiration might result in higher canopy temperatures that can exacerbate heat stress (Kimball, 2016). The effects of CO_2 fertilization are anyway reduced in case of nitrogen and water limitation (Kimball, 2016), which is a common situation in most developing countries.

Climate change has been postulated to be responsible for significant reductions of observed maize yield trends (Lobell et al., 2011) albeit proportionally small compared to the increase related to the agronomical improvements (Ray et al., 2012). However, considering that maize production is stagnating in nearly 26% of the producing areas, global production may become insufficient to meet the projected demand from rising population (Ray et al., 2013). Moreover, water availability for irrigation may become an increasingly critical limiting factor (Scanlon et al., 2012). Notably, in most assessments of climate change impacts on crops, maize stands out to be the most negatively affected (Deryng et al., 2014; Iizumi et al., 2017; Tebaldi & Lobell, 2018).

These concerns motivate our analysis, which adopts statistical methods able to explain a significant portion of the observed interannual production variability (Frieler et al., 2017; Ray et al., 2015; Zampieri, Ceglar, Dentener, & Toreti, 2017). As in similar studies (Lobell, Schlenker, & Costa-Roberts, 2011; Tebaldi & Lobell, 2018), we adopt a statistical approach to estimate the impacts of climate anomalies (namely, heat stress and drought) on the observed crop production variability and trend. Differently from previous studies, we focus on production instead of yield, in order to account also for the effects of climate anomalies on the harvested area (Cohn et al., 2016). The statistical method is then applied to future conditions, influenced by climate change.

For long-term future climate change projections, the validity of the statistical model (inferred with observed data) is questionable when climatic anomalies fall outside the range of values used for its estimation. However, these models can be still applied for near-real-term future projections (Lobell & Asseng, 2017; Tebaldi & Lobell, 2018).

Previous global model studies relied on relatively coarse-resolution climate data, while high-resolution data for impact studies were available at the regional level only. In this study, we compute the statistical indicators on a novel ensemble of high-resolution (approximately 50 km) global climate projections (Dosio et al., 2018; Naumann et al., 2018) and we limit the analysis to the period when the projected climatic anomalies are expected to become comparable with the most intense climate extremes observed in the past. By focusing the analysis on the near future (2020s and 2030s), we also reduce the uncertainty associated with unknown adaptation practices and uncertainties in the sensitivities of plant physiological processes to other climate related factors, such as atmospheric CO_2 concentration (Tebaldi & Lobell, 2018).

2. Materials and Methods

2.1. Definition of the Heat and Water Stress Indexes and Description of the Statistical Model

In a statistical framework, the main effects of climate anomalies can be diagnosed through heat and water stress indicators, here the Heat Magnitude Day (HMD; Zampieri et al., 2016, 2018; Zampieri, Ceglar, Dentener & Toreti, 2017) and the Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2013). These two indicators are computed for a specific period before harvesting, encompassing the flowering stage and the grain filling period (Ceglar et al., 2018; Zampieri, Cegla, Dentener & Toreti, 2017). The HMD integrates the amplitude and duration of maximum daily temperature anomalies exceeding the 90th percentile, which is seasonally and spatially varying. The SPEI is a standardized index cumulating precipitation and evapotranspiration to estimate the state of soil moisture. The nonparametric nature of these indicators bears the advantage of automatically removing the possible biases in the climatic data (Naumann et al., 2018; Zampieri et al., 2018; Zampieri, Ceglar, Dentener & Toreti, 2017) as well as preserving the consistency among atmospheric variables (Naumann et al., 2018).

Time series of heat and water stress indicators are computed on a spatial grid according to the periods defined in the global cropping calendar data set MIRCA 2000 (Portmann et al., 2010). Spatial aggregations at country level are employed using the harvested area information included in the MIRCA 2000 data set as weighting factor, and the harvesting month as reference for the period when the heat and water stress indicators are computed (see Figure S1).

Like previous statistical studies for maize (Ceglar et al., 2018), we use a two-month time window for computing the HMD and a four-month window for the SPEI, both counting backward from the second month before harvesting. Thus, the period after ripening, when the crop is left in the field to dry up and is not any more sensitive to climate variations, is excluded. This approach obviously excludes crop losses associated with field accessibility under extremely wet conditions. Several studies have considered seasonally averaged correlations with crop yields (Iizumi & Ramankutty, 2016; Lobell, Bänziger, et al., 2011; Ray et al., 2015; Tebaldi & Lobell, 2018). Compared to the mean seasonal temperature anomalies computed on the same period, the HMD is more sensitive to warm temperature anomalies and extremes while it is less sensitive to cold anomalies. The HMD is statistically equivalent to the mean seasonal temperature anomalies for small departures from the climatology (see Figure S2 and Text S1).

The combination of HMD and SPEI (i.e., the so-called Combined Stress Index (CSI; Zampieri, Ceglar, Dentener & Toreti, 2017) indirectly also takes into account the effects of other correlated drivers of yield anomalies related to meteorological variations, such as solar radiation, acceleration of phenological stages, weeds, pests, and diseases (Leng et al., 2016; Lobell & Gourdji, 2012; Zampieri et al., 2018).

When focusing on the interannual yield variation, assuming constant harvested area and removing the baseline trend of yields and climate indexes, the CSI explains 50% of maize yield interannual variability in Europe (Ceglar et al., 2018).

The signal of climate variability on harvested area and production can be sometimes larger than that on yield alone (Cohn et al., 2016). In order to take into account the effects of climate variability on the harvested area as well, we consider the production time series instead of yields. Thus, we decompose the observed (FAOSTAT, 2017) country-level production annual time series (P) into an annually varying CSI-driven component and a slowly varying component due to nonclimatic and other external factors (P_{NC}):

$$P = P_{\mathrm{CSI}} + P_{\mathrm{NC}} + \varepsilon \tag{1}$$

$$P_{\mathrm{CSI}} = \alpha \cdot \mathrm{CSI} \equiv \beta \cdot \mathrm{HMD} + \gamma \cdot \mathrm{SPEI} \tag{2}$$

In equation (1), ε represents the residual error component. In equation (2), β and γ are regression coefficients. The calibrated linear combination of HMD and SPEI is the CSI (Ceglar et al., 2018; Zampieri, Ceglar, Dentener & Toreti, 2017), which is proportional to the production loss P_{CSI} through the α coefficient.

We adopt an iterative procedure to determine P_{CSI} and P_{NC}. The algorithm consists of computing

- a first estimate of the climate component (P_{CSI}) using equation (2) evaluated with first guesses of the parameters β and γ obtained from bilinear regression on the production anomalies after removing a linear trend;
- $P_{\mathrm{NC}} + \varepsilon$ using equation (1);
- P_{NC} by using the LOESS method (Cleveland & Devlin, 1988);
- the production anomalies with respect to P_{NC}; and
- a more accurate estimate of the P_{CSI} parameters using bilinear regression on the production anomalies.

This procedure converges quickly after a few iterations, providing the final estimates of β and γ for each country. The CSI iterative algorithm is equivalent to statistical methods including time as regressor for

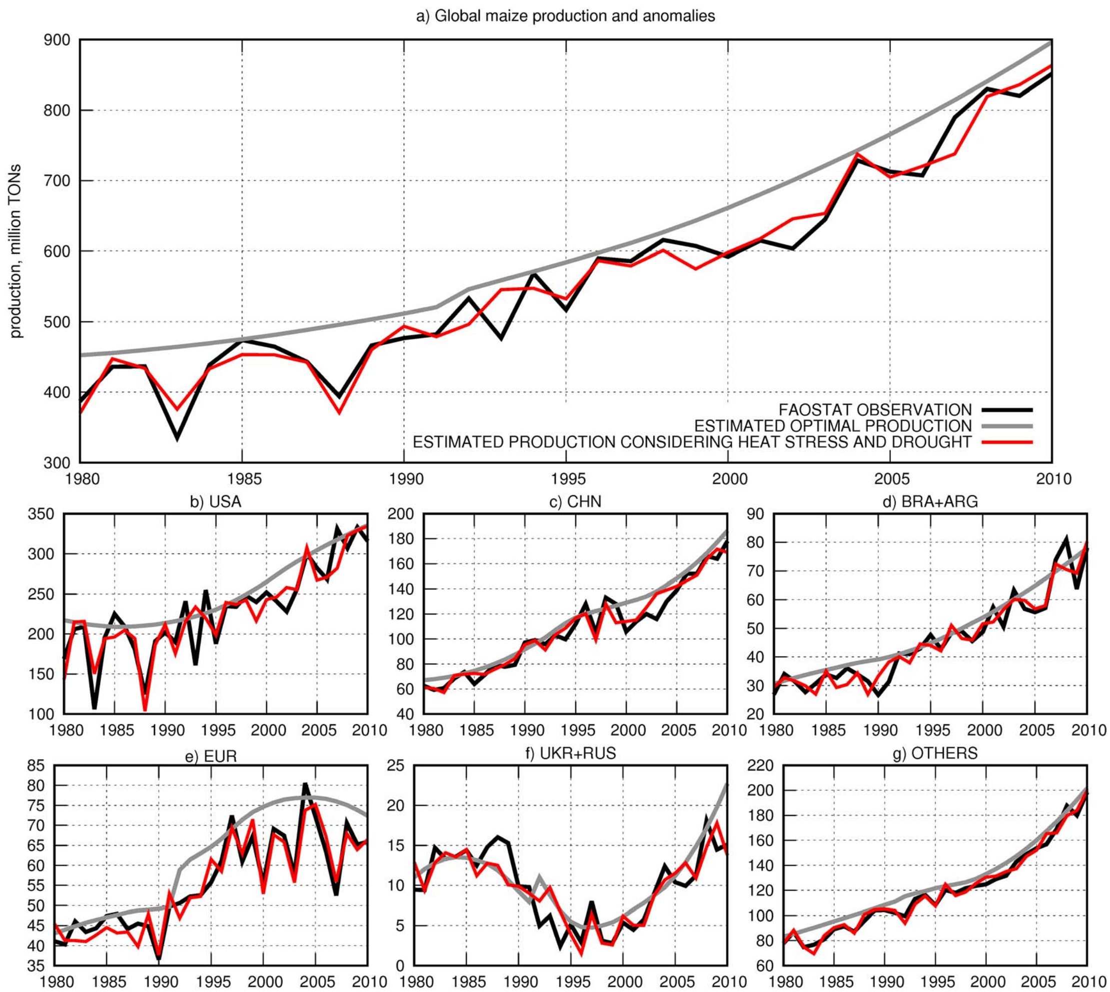

Figure 1. Time series of observed maize production (FAOSTAT; black lines), estimated optimal component (P_{NC}; gray lines) and estimated optimal component minus the anomalies due to heat stress and drought ($P_{NC} - P_{CSI}$; in red) for (a) global, (b) United States, (c) China, (d) the sum of Brazil and Argentina, (e) the sum of all countries of the European Union (EU28), (f) the sum of Ukraine and Russia, and (g) the sum of other smaller producing countries.

linear technological trends in the production time series (e.g., Lobell, Schlenker, & Costa-Roberts, 2011), but it also allows to disentangle the signal due to the climatic anomalies from the nonlinear technological trends (see Figures S3 and S4a–S4c and Text S2).

SPEI is often the dominant predictor in the tropics, indicating larger sensitivity of maize production to drought events. In contrast, in the middle latitude and especially in the United States, the HMD is often the best predictor indicating larger sensitivity to heat stress (Figure S4c).

The nonclimatic component (P_{NC}) is referred as "Estimated Optimal Production" in the Graphical abstract and in Figure 1. The gray dots in the graphical abstract are obtained removing the sum of the losses estimated by the CSI at country level from the FAOSTAT global production records (FAOSTAT, 2017).

2.2. Application to Climate Simulations

We use the statistically derived parameters characterizing the production losses simulated in the period 1980–2010 to interpret the projected changes of heat stress and drought. For each country, the 90th percentile values of the CSI-related production losses (corresponding to the 10-year return period events) computed over period 1980–2010 for each simulation are used to characterize the worse events. For each simulation, we diagnose the timings after 2010 when these values are reached by the 11-year running means of the

Table 1
Skill of the CSI Iterative Model in Capturing the Observed Production Anomalies With Respect to the Estimated Optimal Baselines (R^2)

	World	United States	China	Bra + Arg	Europe	Ukr + Rus	Others
R^2	0.49	0.42	0.33	0.36	0.75	0.51	0.51
P_{CSI} trend	0.00	0.49	−0.21	0.03	−0.29	−0.11	−0.08
p value	0.99	0.36	0.09	0.65	0.01	0.01	0.43

Note. Production trend due to climate (PCSI trend; in million tons per year), with the corresponding p values.

projected production losses, both for each country and for regional aggregates. To summarize the results, we report the median of these estimates.

3. Data

3.1. Data for Calibration in the Reference Period

We use annual production data at country level (FAOSTAT, 2017), available for the period 1971–2016. The meteorological conditions in the calibration period are taken from a bias-corrected reanalysis developed specifically for crop model applications (AgMERRA; Ruane et al., 2015), available from 1980 to 2010, at $0.25 \times 0.25°$ resolution. In the following we call these data "observations."

3.2. Climate Model Outputs

The HMD and the SPEI are computed for seven realizations of historical climate conditions and future climate projections from global climate models downscaled at higher resolution in the context of the High-End cLimate Impacts and eXtremes project (HELIX; https://www.helixclimate.eu/) for the period 1971–2100. The simulations were performed with the SMHI EC-EARTH global atmospheric model at a horizontal resolution of around 50 km. The sea surface temperature and sea ice were prescribed using the output of seven general circulation models (GCMs) from the Coupled Model Intercomparison Project Phase 5 (CMIP5) ensemble (Taylor et al., 2012). The greenhouse gas concentration scenario considered in these simulations (i.e., the RCP8.5) assumes a CO_2 equivalent of about 1,370 ppm and a corresponding warming of approximately 4.0 °C with respect to preindustrial temperatures by the end of the twenty-first century (van Vuuren et al., 2011), which allows evaluating climate change effects under low as well as high levels of warming.

This data set has been used in earlier publications to estimate future changes of heat waves (Dosio et al., 2018) and drought (Naumann et al., 2018). We also validate the climate simulation for the specific purposes of this study by comparing the HMD and the SPEI mean values and the values characterized by a return period of 10 years computed on the simulation ensemble with respect to the same values computed from the observations (see Figure S4 and Text S4).

The final results of the timings when worse maize losses of the past become normal are discussed in comparison with the timings when the different levels of global warming are reached in the simulations (see Text S3 and Table S1).

4. Results

Figure 1a shows the observed global production (i.e., the sum of production in all maize-producing countries) for 1980–2010 and the estimated optimal production. The time series including the anomalies due to heat stress and drought are qualitatively similar to the observations. However, the CSI model skill in capturing the observed anomalies depends on the region (see Table 1 and Figures S4a and S4b). The corresponding trend in production losses is reported in Table 1.

Globally, the sum of the country-level production anomalies estimated by the CSI captures 49% of the variance, in agreement with previous studies (Ceglar et al., 2018; Ray et al., 2015).

In the United States (Figure 1b; 42% variance explained), the observed production losses and those explained by the CSI are higher at the beginning of the time series, consistently with the observed reduction in high-temperature extremes (Troy et al., 2015). Interestingly, in addition to a trend due to technological progress of

Table 2
The 90th Percentile of Observed and Simulated Production Losses Estimated by the CSI, Corresponding to the 10-Year Return Levels of Maize Losses Due to Climate Anomalies in the Period 1980–2010, in Million Tons, and Years when the Same Values Are Reached by the 11-Year Running Means in the Individual Projections of the HELIX Ensemble (see Figure 2)

	World	United States	China	Bra + Arg	Europe	Ukr + Rus	Others
Obs 90th	88	70	12	5.4	14	1.8	9.5
Ens#1 90th	117 (2028)	71 (2033)	15 (2031)	11 (2020)	20 (2041)	3.7 (never)	17 (2014)
Ens#2 90th	100 (2019)	66 (2024)	17 (2050)	10 (2031)	19 (2022)	3.5 (2088)	19 (2021)
Ens#3 90th	129 (2032)	93 (2058)	16 (2035)	11 (2025)	16 (2019)	3.0 (2052)	19 (2019)
Ens#4 90th	96 (2025)	71 (2051)	13 (2026)	10 (2020)	16 (2053)	4.3 (never)	16 (2017)
Ens#5 90th	90 (2030)	52 (2038)	15 (2029)	12 (2029)	17 (2048)	3.1 (never)	20 (2023)
Ens#6 90th	114 (2028)	57 (2040)	16 (2028)	11 (2022)	17 (2036)	3.1 (2094)	17 (2018)
Ens#7 90th	101 (2022)	71 (2050)	14 (2026)	12 (2036)	19 (2022)	3.6 (2083)	20 (2031)

Note. The 90th percentile is not reached until 2100 in the aggregated Ukraine and Russia production projections in some of the ensemble members. The median, the earlier, and the later timings are shown in Figure S5 for each country.

4.4×10^6 t per year, we compute a positive trend of 0.49×10^6 t per year due to decreasing intensity of climate anomalies, consistently with the finding of a recent study by Kukal & Irmak (2018). However, this climatic driven trend is not statistically significant when compared to the interannual production variability, in agreement with Lobell, Bänziger, et al. (2011).

In the EU28 (i.e., the 28 member states of the European Union; Figure 1e), the CSI captures a large fraction (75%) of the variance of the interannual production anomalies. The production losses due to heat and water stress are well captured especially after the 1990s, when climate started to warm faster in western and southern Europe (Zampieri et al., 2013; Zampieri, Toreti, Schindler, Scoccimarro, & Gualdi, 2017). The production of the EU28, without the intensification of the climatic stress, would have reached an additional production trend of 0.29×10^6 t per year larger than the one actually observed. For the EU28, our estimations suggest a nonlinear nonclimatic component consisting of a quick increase in the first half of the period and a stagnation or a small decline afterward, confirming the results of Hawkins et al. (2013) for France, the most important maize producer of the EU. Agronomical reasons (politically and economically driven) might explain the yield stagnation in Europe (e.g., Brisson et al., 2010).

European, Ukrainian and Russian production time series are affected by discontinuities due to the fall of Yugoslavia and of the Communist block. On the contrary, the P_{CSI} time series, being reconstructed on climatic data available from 1980, are homogeneous. Over Ukraine and Russia, the CSI detects a progressively detrimental effect of climate variability in terms of increasing heat and water stress in the last years of the observed period that is responsible for a production trend of −0.11 t per year. The trend in Ukraine and Russia is influenced by the 2010 heat wave event (Zampieri et al., 2016).

An increasing influence of climate variability is found in China as well, consistently with previous estimates (Lobell, Schlenker, & Costa-Roberts, 2011). There, the CSI explains only one third of interannual variance, which is less than in other regions. The global maize loss trend predicted by the CSI over Europe, China, and the other countries is about half million tons per year and it is completely balanced by the trend recorded in the United States.

Table 2 upper row displays the 10-year return levels (90th percentile) of production losses estimated by the CSI based on observations from 1980 to 2010. The next seven rows in Table 2 display the production losses in the reference period, as well as the year when these production losses become the norm in the future. We quantify the latter by calculating the year when the median of the 11-year running means of the seven individual members of the climate simulations ensemble reaches the production loss for the historical period. In the calibration period, the model calculated production losses are generally consistent with the observations, but the global production losses estimated by the CSI tend to somewhat exceed the observed values, probably because of the overestimation of drought impact amplitude (see Figure S3). The 10-year return level values recorded in the United States are quite well represented in the simulation ensemble.

Figure 2 shows the production losses computed through the CSI for the seven-member ensemble of climate change simulations from 1980 to 2100. Table S1 lists the years corresponding to the global warming level timings and discuss their computations in the simulations' ensemble.

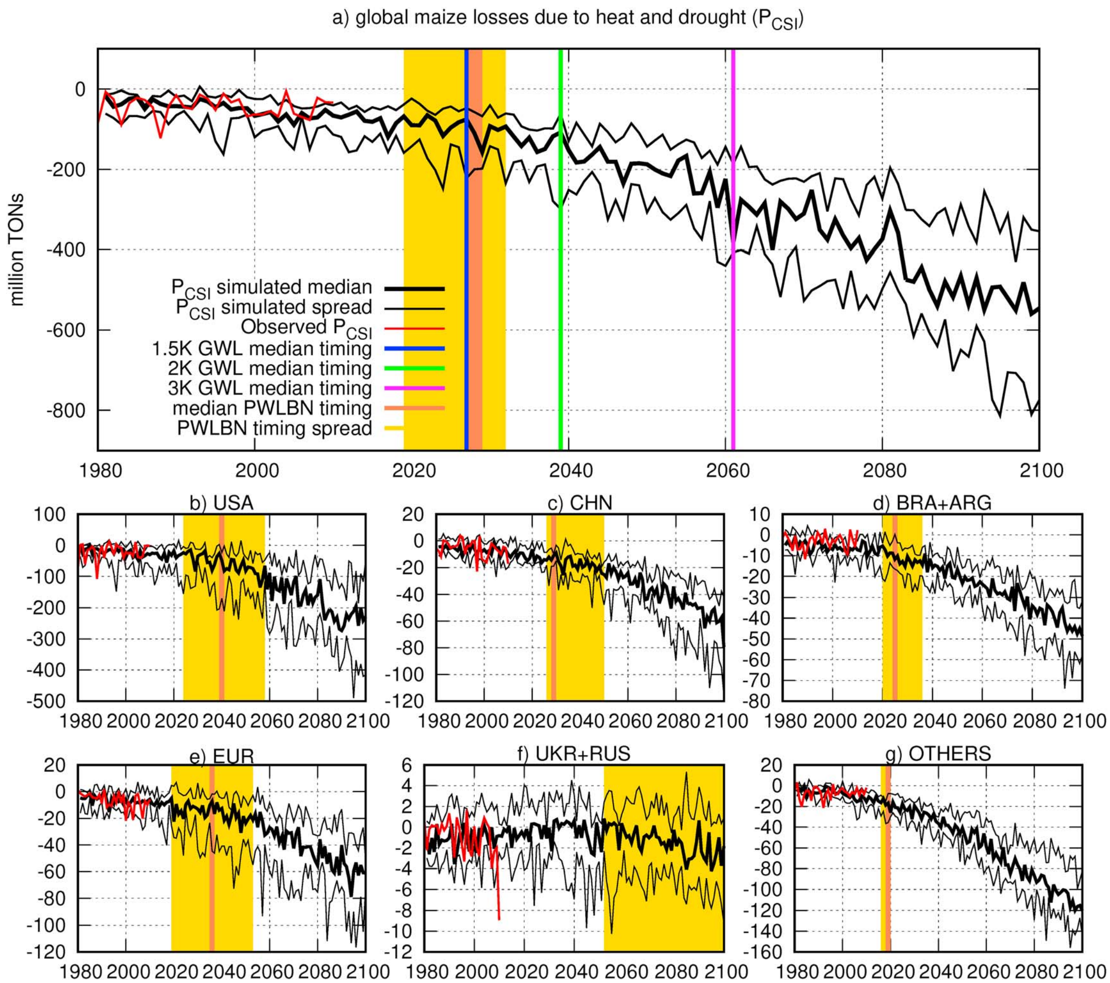

Figure 2. Maize production losses due to heat and water stress (P_{CSI}) in the historical and future climate simulations according to the RCP8.5 emission scenario (the full range is given by the thin black lines, with the bold line representing the median). The time series represented by the red lines are the estimated production losses due to climate in the observations. Light-orange bands indicate the period when the past worse largest losses become normal (PWLBN), that is, when the 10-year return level production losses (estimated on the period 1980–2010) are reached by the 11-year running mean in the simulations. The orange vertical bands represent the median timing of the ensemble. Vertical blue, green, and purple lines in the (a) indicate the median timings when the 1.5, 2, and 3 °C global warming levels (GWL) are reached in the climate simulation ensemble (see Table S1 and Text S3).

At the global level, the effects of climate change on maize production are likely to be comparable to the large historical crop losses already in the next decade (2020–2030) in some of the simulation ensemble members. The median timing when the worse losses simulated in the past are reached almost coincides with the median timing of the 1.5 °C global warming level. We note that in our analysis we assume that current management practices will also be applied in the next decade (i.e., no adaptation). When the 2 °C global warming level is reached, climate change is expected to produce unprecedented losses in global maize production, as indicated in all simulations. At 3 °C global warming level (about 2060 in our model simulations) the situation is even worse. However, in this case the statistical parameters of our model are beyond the "training" range of validity, and results should be considered with caution. Other environmental factors, such as elevated atmospheric CO_2 concentration and changes in fertilization, may become important as well (Tebaldi & Lobell, 2018). Most importantly, by that time significant adaptation measures will likely be adopted.

The effect of CO_2 on production due to the increased water use efficiency (Bassu et al., 2014; Deryng et al., 2014), but also increased sensitivity to temperature (Kimball, 2016), can be roughly estimated in our framework by disentangling the effects of heat stress from drought (Figure S6).

Heat stress is the most important driver of the CSI changes in the United States (Figure S6b). In contrast, drought seems to be responsible for significant losses of maize production in China, Brazil, and Argentina, and the group of the smaller producers (Figures S6c, S6e, and S6g), which could be in principle benefited by CO_2 increase. Large production losses are projected to happen comparatively earlier in China, Europe, and Brazil-Argentina (Figures S6b, S6d, and S6e) with respect to the other regions. The largest relative production losses are found for minor producers (Figure S6g). Notably, climate change is favoring maize production in Ukraine and Russia (Figure S6f) due to a compensation effect between projected increasing heat and decreasing water stress (Figure S6f).

5. Discussion and Conclusions

The statistical model adopted in this study, relating interannual variability and trend of maize production losses to heat and water stress, leads to results consistent with prior analyses on climate impact on crop yield (Lobell, Bänziger, et al., 2011). In particular, our study corroborates the finding that in the period 1980–2010 increasing losses due to climate variability observed in most parts of the world have been compensated by lower variability in the U.S. maize production (Kukal & Irmak, 2018). This production stability was associated with large increases in irrigation capacity (Troy et al., 2015) leading to unsustainable groundwater depletion (Scanlon et al., 2012).

This situation may be changing. The severe 2012 drought in the United States caused maize production losses similar to those in the 1980s (Boyer et al., 2013), which raises question on the resilience of maize production under future climate change conditions.

Statistical crop modeling can provide reliable estimates of the expected impacts of near-term climate change (Lobell & Asseng, 2017; Tebaldi & Lobell, 2018), provided that the climate change is not far beyond the current climate variability. Here we used an ensemble of climate model simulations for 1971–2100 under the RCP8.5 scenario at a global resolution of approximately 50 km. Compared to earlier studies, climate model simulations have higher horizontal global resolution and the applied method is less dependent on climate model biases.

To demonstrate the importance of future climate impacts, we compared the timings when the most detrimental climatic events (10-year return level) affecting maize production in the past become normal in the future. We found that global warming will substantially increase the risk of maize production losses in most world regions, including the United States. The climatic events affecting historical global maize production once every 10 years will become normal at the 1.5 °C global warming level, which is reached in the 2020s in most of the analyzed climate model simulations. This global signal is mostly driven by the U.S. production. In contrast, maize production is projected to be relatively stable in Ukraine and Russia across the twenty-first century driven by compensating impacts of reduced water stress and increasing temperature. Our analysis suggests an alarming situation for several other regions, which to a large extent rely on maize for human consumption, livestock feed, and biofuel production.

At the 2 °C warming level (approximately late 2030s), our projections suggest that global maize production will suffer from unprecedented losses, if no adaptation practices will be adopted. Efforts are advisable to identify new regions suitable for maize cultivation (Davis et al., 2017; Leng & Huang, 2017; Ramirez-Cabral et al., 2017), as well as to develop efficient and sustainable adaptation strategies (Muller et al., 2015; Scanlon et al., 2012). Adaptation and relocation of production strategies have to account for other sustainability goals, including reducing GHG emissions and other environmental pressures (i.e., less fertilization) and optimize water use. Better understanding of several major uncertainties (i.e., CO_2 and canopy effects; Kimball et al., 2016) is needed.

Acknowledgments
M.Z. conceived the idea and designed the study; A. T., A. C., and F. D. contributed to the design of the study; M.Z. and G.N. performed the computations; and A.D. retrieved the data of the climate projections. All authors reviewed and contributed significantly to the manuscript. Climate simulations were performed under the Helix Climate High-End cLimate Impacts and eXtremes project (HELIX; FP7 id 603864)—https://www.helixclimate.eu/. HELIX data are available at http://data.europa.eu/89 h/jrc-climate-spei-drought-helix-ec-earth-1975-2100 and upon request; the other data used in this paper are publicly available. The authors declare no conflicts of interests.

References

Barnabas, B., Jager, K., & Feher, A. (2008). The Effect of Drought and Heat Stress on Reproductive Processes in Cereals. *Plant, Cell and Environment*, *31*, 11–38.

Bassu, S., Brisson, N., Durand, J. L., Boote, K., Lizaso, J., Jones, J. W., et al. (2014). How do various maize crop models vary in their responses to climate change factors? *Global Change Biology*, *20*(7). https://doi.org/10.1111/gcb.12520

Boyer, J. S., Byrne, P., Cassman, K. G., Cooper, M., Delmer, D., Greene, T., et al. (2013). The U.S. drought of 2012 in perspective: A call to action. *Global Food Security*, *2*(3), 139–143. https://doi.org/10.1016/j.gfs.2013.08.002

Brisson, N., Gate, P., Gouache, D., Charmet, G., Oury, F. X., & Huard, F. (2010). Why are wheat yields stagnating in Europe? A comprehensive data analysis for France. *Field Crops Research*, *119*(1), 201–212. https://doi.org/10.1016/j.fcr.2010.07.012

Ceglar, A., Toreti, A., Prodhomme, C., Zampieri, M., Turco, M., & Doblas-Reyes, F. J. (2018). Land-surface initialisation improves seasonal climate prediction skill for maize yield forecast. *Scientific Reports*, *8*(1), 1–9. https://doi.org/10.1038/s41598-018-19586-6

Cleveland, W. S., & Devlin, S. J. (1988). Locally weighted regression: An approach to regression analysis by local fitting. *Journal of the American Statistical Association*, *83*(403), 596–610. https://doi.org/10.2307/2289282

Cohn, A. S., Vanwey, L. K., Spera, S. A., & Mustard, J. F. (2016). Cropping frequency and area response to climate variability can exceed yield response. *Nature Climate Change*, *6*(6), 601–604. https://doi.org/10.1038/nclimate2934

Crafts-Brandner, S. J., & Salvucci, M. E. (2002). Sensitivity of photosynthesis heat stress in a C4 plant, maize to heat stress, *Plant Physiology*, *129*(4), 1773–1780. https://doi.org/10.1104/pp.002170.or

Davis, K. F., Rulli, M. C., Seveso, A., & D'Odorico, P. (2017). Increased food production and reduced water use through optimized crop distribution. *Nature Geoscience*, *10*(12), 919–924. https://doi.org/10.1038/s41561-017-0004-5

Deryng, D., Conway, D., Ramankutty, N., Price, J., & Warren, R. (2014). Global crop yield response to extreme heat stress under multiple climate change futures. *Environmental Research Letters*, *9*(3). https://doi.org/10.1088/1748-9326/9/3/034011

Dosio, A., Mentaschi, L., Fischer, E. M., & Wyser, K. (2018). Extreme heat waves under 1.5 °C and 2 °C global warming. *Environ. Res. Lett.*, *13*, 054006. https://doi.org/10.1088/1748-9326/aab827

FAOSTAT. (2017). Faostat dataset. Retrieved from http://www.fao.org/faostat/

Frieler, K., Schauberger, B., Arneth, A., Balkovic, J., & Chryssanthacopoulos, J. (2017). Understanding the weather—signal in national crop—yield variability. *Earth's Future*, *5*(6), 606–616.

Gourdji, S. M., Sibley, A. M., & Lobell, D. B. (2013). Global crop exposure to critical high temperatures in the reproductive period: Historical trends and future projections. *Environmental Research Letters*, *8*(2), 0–10. https://doi.org/10.1088/1748-9326/8/2/024041

Hawkins, E., Fricker, T. E., Challinor, A. J., Ferro, C. A. T., Ho, C. K., & Osborne, T. M. (2013). Increasing influence of heat stress on French maize yields from the 1960s to the 2030s. *Global Change Biology*, *19*(3), 937–947. https://doi.org/10.1111/gcb.12069

Iizumi, T., Furuya, J., Shen, Z., Kim, W., Okada, M., Fujimori, S., et al. (2017). Responses of crop yield growth to global temperature and socioeconomic changes. *Scientific Reports*, *7*(1), 7800. https://doi.org/10.1038/s41598-017-08214-4

Iizumi, T., & Ramankutty, N. (2016). Changes in yield variability of major crops for 1981–2010 explained by climate change. *Environmental Research Letters*, *11*, 0. https://doi.org/10.1088/1748-9326/11/3/034003

Kimball, B. A. (2016). Crop responses to elevated CO_2 and interactions with H_2O, N, and temperature. *Current Opinion in Plant Biology*, *31*, 36–43. https://doi.org/10.1016/j.pbi.2016.03.006

Klopfenstein, T. J., Erickson, G. E., & Berger, L. L. (2013). Maize is a critically important source of food, feed, energy and forage in the USA. *Field Crops Research*, *153*, 5–11. https://doi.org/10.1016/j.fcr.2012.11.006

Kukal, M. S., & Irmak, S. (2018). Climate-driven crop yield and yield variability and climate change impacts on the U.S. Great Plains agricultural production. *Scientific Reports*, (November 2017), 1–18. https://doi.org/10.1038/s41598-018-21848-2

Leng, G., & Huang, M. (2017). Crop yield response to climate change varies with crop spatial distribution pattern. *Scientific Reports*, *7*(1), 1–10. https://doi.org/10.1038/s41598-017-01599-2

Leng, G., Zhang, X., Huang, M., Asrar, G. R., & Leung, L. R. (2016). The role of climate covariability on crop yields in the conterminous United States. *Scientific Reports*, *6*(September), 1–11. https://doi.org/10.1038/srep33160

Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, *529*(7584), 84–87. https://doi.org/10.1038/nature16467

Lobell, D. B., & Asseng, S. (2017). Comparing estimates of climate change impacts from process-based and statistical crop models. *Environmental Research Letters*, *12*, 1–12. https://doi.org/10.1088/1748-9326/015001

Lobell, D. B., Bänziger, M., Magorokosho, C., & Vivek, B. (2011). Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nature Climate Change*, *1*(1), 42–45. https://doi.org/10.1038/nclimate1043

Lobell, D. B., & Gourdji, S. M. (2012). The influence of climate change on global crop productivity. *Plant Physiology*, *160*(4), 1686–1697. https://doi.org/10.1104/pp.112.208298

Lobell, D. B., Hammer, G. L., McLean, G., Messina, C., Roberts, M. J., & Schlenker, W. (2013). The critical role of extreme heat for maize production in the United States. *Nature Climate Change*, *3*(5), 497–501. https://doi.org/10.1038/nclimate1832

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. *Science*, *333*(6042), 616 LP–620. Retrieved from http://science.sciencemag.org/content/333/6042/616.abstract

Makowski, D., Asseng, S., Ewert, F., Bassu, S., Durand, J. L., Li, T., et al. (2015). A statistical analysis of three ensembles of crop model responses to temperature and CO_2 concentration. *Agricultural and Forest Meteorology*, *214–215*, 483–493. https://doi.org/10.1016/j.agrformet.2015.09.013

Matiu, M., Ankerst, D. P., & Menzel, A. (2017). Interactions between temperature and drought in global and regional crop yield variability during 1961–2014. *PLoS One*, *12*(5), 1–23. https://doi.org/10.1371/journal.pone.0178339

Muller, C., Elliott, J., Chryssanthacopoulos, J., Deryng, D., Folberth, C., Pugh, T., & Schmid, E. (2015). Implications of climate mitigation for future agricultural production. *Environmental Research Letters*, *10*(12), 125004. https://doi.org/10.1088/1748-9326/10/12/125004

Naumann, G., Alfieri, L., Wyser, K., Mentaschi, L., Betts, R. A., Carrao, H., et al. (2018). Global changes in drought conditions under different levels of warming. *Geophysical Research Letters*, *45*, 3285–3296. https://doi.org/10.1002/2017GL076521

Ramirez-Cabral, N. Y. Z., Kumar, L., & Shabani, F. (2017). Global alterations in areas of suitability for maize production from climate change and using a mechanistic species distribution model (CLIMEX). *Scientific Reports*, *7*(1), 1–13. https://doi.org/10.1038/s41598-017-05804-0

Ranum, P., Peña-Rosas, J. P., & Garcia-Casal, M. N. (2014). Global maize production, utilization, and consumption. *Annals of the New York Academy of Sciences*, *1312*(1), 105–112. https://doi.org/10.1111/nyas.12396

Ray, D. K., Gerber, J. S., Macdonald, G. K., & West, P. C. (2015). Climate variation explains a third of global crop yield variability. *Nature Communications*, *6*, 1–9. https://doi.org/10.1038/ncomms6989

Ray, D. K., Mueller, N. D., West, P. C., & Foley, J. A. (2013). Yield trends are insufficient to double global crop production by 2050. *PLoS ONE*, *8*(6). https://doi.org/10.1371/journal.pone.0066428

Ray, D. K., Ramankutty, N., Mueller, N. D., West, P. C., & Foley, J. A. (2012). Recent patterns of crop yield growth and stagnation. *Nature Communications*, *3*, 1293–1297. https://doi.org/10.1038/ncomms2296

Ray, J. D., Gesch, R. W., Sinclair, T. R., & Hartwell Allen, L. (2002). The effect of vapor pressure deficit on maize transpiration response to a drying soil. *Plant and Soil*, *239*(1), 113–121. https://doi.org/10.1023/A:1014947422468

Ruane, A. C., Goldberg, R., & Chryssanthacopoulos, J. (2015). Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation. *Agricultural and Forest Meteorology*, *200*, 233–248. https://doi.org/10.1016/j.agrformet.2014.09.016

Sánchez, B., Rasmussen, A., & Porter, J. R. (2014). Temperatures and the growth and development of maize and rice: A review. *Global Change Biology*, *20*(2), 408–417. https://doi.org/10.1111/gcb.12389

Scanlon, B. R., Faunt, C. C., Longuevergne, L., Reedy, R. C., Alley, W. M., McGuire, V. L., & McMahon, P. B. (2012). Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley. *Proceedings of the National Academy of Sciences*, *109*(24), 9320–9325. https://doi.org/10.1073/pnas.1200311109

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, *106*(37), 15,594–15,598. https://doi.org/10.1073/pnas.0906865106

Schleussner, C. F., Deryng, D., Müller, C., Elliott, J., Saeed, F., Folberth, C., et al. (2018). Crop productivity changes in 1.5 °C and 2 °C worlds under climate sensitivity uncertainty. *Environmental Research Letters*, *13*(6). https://doi.org/10.1088/1748-9326/aab63b

Semenov, M. a., & Shewry, P. R. (2008). Comment on Lobell et al "Climate trends and global crop production since 1980". *Nature Precedings*, 1–5. https://doi.org/10.1038

Shiferaw, B., Prasanna, B. M., Hellin, J., & Bänziger, M. (2011). Crops that feed the world 6. Past successes and future challenges to the role played by maize in global food security. *Food Security*, *3*(3), 307–327. https://doi.org/10.1007/s12571-011-0140-5

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, *93*(4), 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1

Tebaldi, C., & Lobell, D. (2018). Differences, or lack thereof, in wheat and maize yields under three low-warming scenarios open access differences, or lack thereof, in wheat and maize yields under three low-warming scenarios. *Environmental Research Letters*, *13*(6), 065001.

Troy, T. J., Kipgen, C., & Pal, I. (2015). The impact of climate extremes and irrigation on US crop yields. *Environmental Research Letters*, *10*(5), 054013. https://doi.org/10.1088/1748-9326/10/5/054013

van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., et al. (2011). The Representative Concentration Pathways: An overview. *Climatic Change*, *109*(1), 5–31. https://doi.org/10.1007/s10584-011-0148-z

Vicente-Serrano, S. M., Gouveia, C., Camarero, J. J., Begueria, S., Trigo, R., Lopez-Moreno, J. I., et al. (2013). Response of vegetation to drought time-scales across global land biomes. *Proceedings of the National Academy of Sciences*, *110*(1), 52–57. https://doi.org/10.1073/pnas.1207068110

Zampieri, M., Ceglar, A., Dentener, F., & Toreti, A. (2017). Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. *Environmental Research Letters*, *12*, 64008. https://doi.org/https://doi.org/10.1088/1748-9326/aa723b

Zampieri, M., Ceglar, A., Dentener, F., & Toreti, A. (2018). Understanding and reproducing regional diversity of climate impacts on wheat yields: Current approaches, challenges and data driven limitations. *Environmental Research Letters*, (February), 37–41. https://doi.org/10.1088/1748-9326/aaa00d

Zampieri, M., D'Andrea, F., Vautard, R., Ciais, P., De Noblet-Ducoudré, N., & Yiou, P. (2009). Hot European summers and the role of soil moisture in the propagation of Mediterranean drought. *Journal of Climate*, *22*(18), 4747–4758. https://doi.org/10.1175/2009JCLI2568.1

Zampieri, M., Russo, S., di Sabatino, S., Michetti, M., Scoccimarro, E., & Gualdi, S. (2016). Global assessment of heat wave magnitudes from 1901 to 2010 and implications for the river discharge of the Alps. *Science of the Total Environment*, *571*, 1330–1339. https://doi.org/10.1016/j.scitotenv.2016.07.008

Zampieri, M., Scoccimarro, E., & Gualdi, S. (2013). Atlantic influence on spring snowfall over the Alps in the past 150 years. *Environmental Research Letters*, *8*(3). https://doi.org/10.1088/1748-9326/8/3/034026

Zampieri, M., Toreti, A., Schindler, A., Scoccimarro, E., & Gualdi, S. (2017). Atlantic multi-decadal oscillation influence on weather regimes over Europe and the Mediterranean in spring and summer. *Global and Planetary Change*, *151*, 92–100. https://doi.org/10.1016/j.gloplacha.2016.08.014

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., et al. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of Sciences*, 201701762. https://doi.org/10.1073/pnas.1701762114

Zipper, S., J, Q., & Kucharik, C. (2016). Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes. *Environmental Research Letters*, *11*(94021). https://doi.org/10.1088/1748-9326/11/9/094021