The effects of climate extremes on global agricultural yields

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Abstract

Climate extremes, such as droughts or heat waves, can lead to harvest failures and threaten the livelihoods of agricultural producers and the food security of communities worldwide. Improving our understanding of their impacts on crop yields is crucial to enhance the resilience of the global food system. This study analyses, to our knowledge for the first time, the impacts of climate extremes on yield anomalies of maize, soybeans, rice and spring wheat at the global scale using sub-national yield data and applying a machine-learning algorithm. We find that growing season climate factors—including mean climate as well as climate extremes—explain 20%–49% of the variance of yield anomalies (the range describes the differences between crop types), with 18%–43% of the explained variance attributable to climate extremes, depending on crop type. Temperature-related extremes show a stronger association with yield anomalies than precipitation-related factors, while irrigation partly mitigates negative effects of high temperature extremes. We developed a composite indicator to identify hotspot regions that are critical for global production and particularly susceptible to the effects of climate extremes. These regions include North America for maize, spring wheat and soy production, Asia in the case of maize and rice production as well as Europe for spring wheat production. Our study highlights the importance of considering climate extremes for agricultural predictions and adaptation planning and provides an overview of critical regions that are most susceptible to variations in growing season climate and climate extremes.

1. Introduction

Different types of climate extremes are projected to intensify and become more frequent in a number of regions worldwide due to climate change (IPCC 2012). Extreme events, such as droughts and heat waves, can adversely impact agricultural production and have implications for the livelihoods and food security of communities. Not only regions immediately experiencing the extreme event are affected, but also regions in other parts of the world, which may suffer from indirect consequences such as reduced exports of agricultural products and higher food prices (GFSP 2015, Puma *et al* 2015). A recent example of the impacts of climate extremes on agricultural productivity is the European heat wave and drought in summer 2018, which lead to widespread harvest failures and shortages of fodder for livestock in many countries across the continent (DW 2018). To secure and optimise yields in a changing climate, it is crucial to understand the impact of climate extremes on crop yields in the past and present climate.

Table 1. Overview of predictor variables.

Variable name	Short name	Description	Data source
Mean temperature	tmp	Mean monthly temperature during the growing season	CRU TS 3.23 (Harris *et al* 2014)
Mean precipitation	pre	Mean monthly precipitation during the growing season	CRU TS 3.23 (Harris *et al* 2014)
Diurnal temperature range	dtr	Mean diurnal temperature range during the growing season	CRU TS 3.23 (Harris *et al* 2014)
Frost day frequency	frs	Mean frost day frequency during the growing season	CRU TS 3.23 (Harris *et al* 2014)
Maximum temperature	TXx	Maximum temperature during the growing season	HadEX2 (Donat *et al* 2013b)
Minimum temperature	TNn	Minimum temperature during the growing season	HadEX2 (Donat *et al* 2013b)
Warm day frequency	TX90p	Percentage of days during the growing season with daily maximum temperature above the 90th percentile	HadEX2 (Donat *et al* 2013b)
Cold night frequency	TN10p	Percentage of days during the growing season with daily minimum temperature below the 10th percentile	HadEX2 (Donat *et al* 2013b)
Maximum 5-day precipitation intensity	Rx5day	Maximum 5-day rainfall intensity during the growing season	HadEX2 (Donat *et al* 2013b)
SPI-6	spi-6	Mean SPI-6 (standard precipitation index for 6-month time interval) during the growing season	Calculated from CRU TS 3.23 precipitation (Harris *et al* 2014)

Previous studies have investigated the impacts of extreme events on crop yields for individual regions for which high-resolution yield and climate data were available (Schlenker and Roberts 2009, Troy *et al* 2015, Lüttger and Feike 2017). Studies focusing on agricultural impacts of climate extremes at the global scale often use nationally aggregated yield data and climate extreme indicators (e.g. Lesk *et al* 2016). While these studies provide valuable insights into the effects of climate extremes on yields at national scale, the spatial aggregation—one yield time series per country—can mask out the effects of more localised extremes, especially in major crop producing countries with large land areas, such as China, the US or Russia, potentially resulting in an under-estimation of their effects. Previous research that combined fine-scale yield statistics with high-resolution climate data focused on estimating the sensitivity of crop yields to climate variability, without looking at the effects of climate extremes specifically (Ray *et al* 2015). To our knowledge, a global study analysing the impacts of climate extremes on crop yields, using yield data at sub-national scale, has not been performed to date.

A major challenge for the analysis of extreme event impacts on global agriculture has been the availability of high-quality yield and climate extremes data at suitable spatial and temporal scales. Extreme events are—by definition—rare, therefore, their analysis requires a sufficiently large number of observations, spanning several decades or including a large dataset of spatially independent data points. Here, we use a global agricultural database providing data at sub-national spatial resolution, combined with global coverage climate and climate extreme indicator datasets, to estimate the effect of temperature and precipitation extremes on yields of the top four global crops (maize, soybeans, rice, wheat—the latter separated into winter and spring wheat), from 1961 to 2008. We predict grid-cell yield anomalies—deviations of yields from an overall trend—using 'Random Forests' (Breiman 2001), a machine learning algorithm that allows for capturing nonlinearities and complex interactions in the investigated statistical relationships between climate extremes and yields. The selected predictors include mean precipitation and temperature as well as extreme event indicators representing warm and cold temperature extremes, drought and heavy precipitation (table 1).

We find that climate variables considered in this study—representing both mean climate conditions and climate extremes during the growing season—explain 20%–49% of the variance of yield anomalies at the global scale (range over all crop types). Climate extremes increase the explained variance of yield anomalies by 18%–43% over what mean conditions may explain, which represents more than half of the explained variance in maize, soybeans and rice. Our study further shows that temperature extremes have a stronger association with yield anomalies than precipitation-related variables such as drought or heavy precipitation indices. Irrigation is found to mitigate negative effects of extreme warm days, particularly for spring wheat and soybeans, which underlines the close link between water availability and the effects of heat extremes found in earlier research. We identify regions that are highly relevant for global production and in

which production variability may be particularly influenced by climate extremes, using a composite indicator built upon the results of the statistical analysis. The regions that are most influenced by climate extremes are North America (for maize, spring wheat and soy production), Asia (maize and rice) and Europe (spring wheat). The results of this study may support efforts to increase the resilience of agricultural production systems by identifying differences in yield sensitivity to climate extremes and by supporting efforts to adapt to climate extremes, including the development or improvement of seasonal forecasts for agriculture.

2. Data

2.1. Agricultural data

We used a global, high-resolution crop yield dataset which includes data of the top four global crops (maize, wheat, rice, soybeans) across ~13 500 spatial units worldwide, spanning the years 1961–2008 (Ray *et al* 2012). The dataset was developed by retrieving agricultural information from public source, statistical bureaus and agricultural agencies and contains time series of production, yields and area harvested for each crop type and administrative unit. Data availability was variable across regions and time periods, with data missing especially in the early years of the available data. Where data were missing, the 5-year average per spatial unit was used to interpolate the time series, constrained by available data of the geographic unit at the next higher level (e.g. the national scale; see Ray *et al* (2012) for further information on the data collection and processing). We separated the wheat yield data into winter and spring wheat based on the distinction provided in the crop calendar by Sacks *et al* (2010, SI section 1.1.1 is available online at stacks.iop.org/ERL/14/054010/mmedia).

2.2. Climate and climate extremes data

To analyse the impacts of mean and extreme climate conditions on crop yields, we used data from the Climatic Research Unit (CRU) TS 3.23 dataset (Harris *et al* 2014) and the HadEX2 extremes indicator dataset (Donat *et al* 2013b) as predictor variables, spanning the same time period as the yield data. These two datasets were used as they are based on observational data, provide meteorological and climate extremes data at monthly resolution, which is required for focusing on the growing season months (the extremes indicators were calculated from daily-scale station data and aggregated to the monthly scale). Both datasets have nearly global coverage and cover several decades back to at least the mid-20th century. This means that relating climate data to the crop dataset is possible, taking advantage of the entire length of record. While the CRU TS 3.23 dataset is available on a 0.5° × 0.5° grid, the HadEX2 data was available on a comparatively coarse 2.5° × 3.75° grid. Other extreme indicator datasets at higher resolution are available, but these either do not provide quasi-global coverage and were not quality controlled to the same extent as the HadEX2 data (e.g. GHCNDEX, Donat *et al* 2013a; see supplementary figure 1 for a comparison of global coverage of HadEX2 and GHCNDEX), or are based on reanalyses data that do not cover the complete time period for which agricultural data is available (e.g. indices based on ERA-Interim, Dee *et al* 2011, starting in 1979; see SI section 1.1.2 for a discussion of the dataset choice).

Climate variables included in our analysis are: mean monthly precipitation, mean monthly near-surface air temperature, mean diurnal temperature range, frost day frequency, extreme indicators from HadEX2 capturing high and low temperature extremes as well as heavy precipitation events (see table 1 for an overview of predictor variables). The high and low temperature predictors measuring the frequency of warm days (TX90p) and cold nights (TN10p) are percentile-based relative to the local temperature distribution, hence thresholds are based on local climate conditions (see Donat *et al* 2013b). We further calculated the SPI-6 index from CRU TS 3.23 precipitation data as a proxy for meteorological drought conditions (table 1).

2.3. Calculation of growing season climate data

The harmonised crop calendar (v1.0) of the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig *et al* 2013) was used to define planting and harvesting dates. We masked this calendar to only include grid cells where published growing season dates from either Sacks *et al* (2010) or the MIRCA2000 dataset (Portmann *et al* 2010) were available. The crop calendar provides different growing season dates for irrigated and rainfed systems for each crop and grid cell. We selected the growing season dates with the dominant irrigation status based on the MIRCA2000 land use dataset (Portmann *et al* 2010). Planting and harvest dates were converted into months; statistical parameters (minimum, mean and/or maximum) were calculated over all months of the growing season, including planting and harvesting months.

2.4. Data processing

All spatial data were re-gridded to a common 1.5° × 1.5° grid by bilinear interpolation to balance the coarse resolution of HadEX2 (2.5° × 3.75°) with the finer 0.5° × 0.5° resolution of all other datasets (see SI section 1.1.4). The regridded time series were detrended using a parameter-free trend estimation method, singular spectrum analysis (Vautard *et al* 1992), implemented in the 'ssa' R package (Zhao 2016), yielding a multi-annual smoothing (see supplementary figure 2 for a comparison of detrending methods). Yield time series were detrended to remove temporal trends due to technological progress and management

changes. Climate time series were detrended assuming that agricultural managers are continuously adapting to changing climate conditions (Butler and Huybers 2013), and climate shocks deviating from the expected trend have the most detrimental effect on yields. Detrended climate predictors and yields were standardised per grid cell by dividing by their standard deviation to account for the fact that grid cells with smaller mean yields tend to have smaller anomalies and assuming that local agriculture is adapted to local mean climate variability (SI section 1.1.5).

All data are publicly available or available on request (see supplementary table 2 for data access).

3. Methods

3.1. Random Forest model and cross-validation

We applied the machine learning algorithm 'Random Forests' (Breiman 2001) to detrended and standardised time series of crop yields and climate predictors to predict crop yield anomalies. The Random Forest algorithm is a non-parametric statistical method, which uses an ensemble of decision trees and can be applied to regression and classification problems (Breiman 2001). Random Forests have previously been applied to the analysis of the influence of climate factors on yields in specific countries or regions (Jeong *et al* 2016, Hoffman *et al* 2017), but an analysis of extreme event impacts at the global scale, using subnational yield data, has not yet been done.

To estimate the variance of yield anomalies explained by climate predictors, we calculated R^2 values from cross-validated out-of-sample predictions (SI section 1.2.3 for further information). We obtained R^2 values from time series at the continental and global scale by calculating aggregated yield anomalies (actual and predicted) as weighted arithmetic mean with harvested area as weighting factors. This calculation ensures that grid cells with large harvesting areas, where yield losses have greater impacts on regional or global production anomalies, contribute more to overall R^2 values—unlike calculating a simple mean R^2 over all grid cells (SI section 1.2.3).

To assess the relative impact of the climate extremes, we subsequently trained a Random Forest on a subset of predictor variables representing only mean climate conditions during the growing season and calculated the differences in explained variance (out-of-sample R^2) as a proxy for the relative influence of extreme event indicators.

We tested the robustness of our results to the choice of statistical learning method by comparing the Random Forest model against four other widely used methods (Support Vector Machine, Generalised additive models, K-Nearest neighbours, and multiple linear regression). While the Random Forest method yielded overall slightly higher explained variances (R^2), we found the results of this study with respect to the yield effects of climate variations and extremes on yields, including the relative importance of climate extremes, to be robust to the choice of statistical method (see SI section 1.4).

3.2. Variable importance and partial dependence plots

The Random Forest algorithm allows for an investigation of relationships between climate variables and yield anomalies by providing the relative variable importance and the functional relationship between each predictor and the target variable (Jeong *et al* 2016). Variable importance values were calculated for each crop type, based on a metric that captures the increase in mean squared error (MSE), calculated from out-of-sample predictions, after randomly permuting the values of the respective predictor. Variable importance values were obtained using the R 'randomForest' library (Liaw and Wiener 2002).

Partial dependence plots visualise the functional relationship between a predictor variable and the response variable after all other predictors are accounted for, similar to a sensitivity test for each predictor. Partial dependence plots were created by randomly sampling 500 observations from the complete dataset of climate observations (pooling all grid cells and time steps) and varying the one predictor variable of interest at 100 equidistant points between its minimum and maximum. After applying the statistical model to the resulting 5000 data points (500 $\times$ 100), we calculated the mean yield response across the whole range of the predictor variable as well as the uncertainty bands of the predictions (see SI section 1.2.7 for further information).

3.3. Sensitivity of regional crop production to climate conditions

To put our findings into the context of global food production, we estimate the contribution of climate factors, and particularly extreme events, to fluctuations in regional crop production. Crop production varies with crop yields (t/ha) and harvested areas (ha). Thus, to estimate the relevance of climate variations to global and regional variances in crop production, we considered: (i) the share of a region's crop production relative to global production, (ii) the mean variability of regional production, (iii) the extent to which production anomalies are associated with yield anomalies (as opposed to variations in harvest area), and (iv) the explained variance of yield anomalies, predicted by fluctuations in climate conditions and specifically extreme events. The four indices are combined into composite indices by calculating the geometric mean of factors i–iv.

A detailed description of the methodological approach and a discussion of limitations can be found in the supplementary information ('Extended methodology' and 'Limitations'). The data processing and

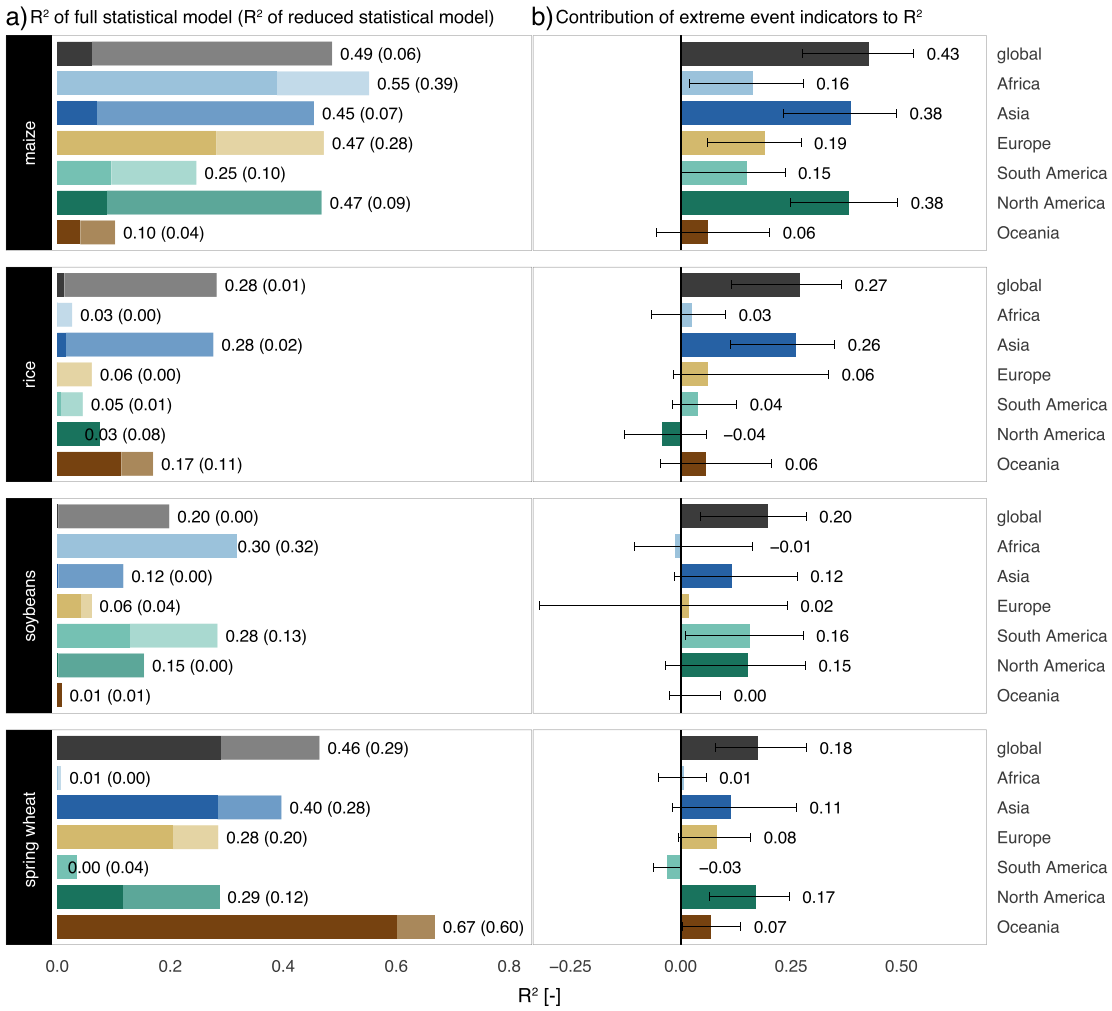

Figure 1. Explained variance (R^2) from Random Forest out-of-sample predictions. (a) Light-coloured bars: R^2 values of the full statistical model accounting for mean climate conditions and extreme events; dark-coloured bars: R^2 of reduced model only accounting for mean climate conditions. (b) Difference in R^2 of full statistical model and reduced model, as an estimation of the partial explained variance from climate extremes indicators. R^2 values were calculated from a regression of predicted yield anomalies against observed yield anomalies; yield anomalies were previously averaged over continents and globally (Methods). The thin bars indicate the 5- to 95-percentile range of the bootstrapped distribution of R^2 differences between the full and reduced statistical models (SI section 1.2.5).

analysis scripts are available online (at https://github.com/elisabethvogel/gs_clim_data for the preparation of the growing season climate data, and https://github.com/elisabethvogel/climate_extremes_agriculture, for the statistical analysis).

4. Results

4.1. Climate conditions explain 20%–49% of the variance of global aggregated yield anomalies

The Random Forest models—including both growing season climate means and extremes as predictors—were able to explain nearly half of the variance of global yield anomalies for maize and spring wheat (49% and 46%, respectively), about one quarter (28%) of yield anomalies for rice and one fifth (20%) for soybeans (figure 1(a); all numerical values shown in supplementary table 3). Explained variances of maize yields were highest among all crops, both globally and for most regions (explained variances between 45% and 55% of variance in all continents, except South America, with 25%, and Oceania, with 10%, see figure 1(a)). For soybeans, explained variances are highest in South America and Africa (28%–30%). For rice, approximately 28% of the variance in yields in Asia is explained by the considered climate variables. Explained variances for spring wheat were highest in Oceania, specifically in Australia with an R^2 of 67%, i.e. about two-third of the variance of observed crop yields can be explained by climate conditions. In contrast, the considered climate indicators can only explain a minor component of observed variations in winter wheat yields (not shown) likely due to the comparatively long growing season spanning several seasons. Therefore, winter wheat was excluded from this analysis.

4.2. Extreme event indicators explain 18%–43% of the variance of yield anomalies, contributing more

than half of the explained variance in maize, soybeans and rice

By comparing the explained variances of the full statistical models to variances explained by reduced models which only account for mean climate conditions, we quantify the fraction of the explained variance that can be attributed to extreme climate conditions. While growing season mean climate conditions captured nearly 30% of the global variability in spring wheat yields, they do not capture any significant part of the variance of maize, soybeans and rice yields (6%, 0% and 1%, respectively; figure 1(a); supplementary table 3). When excluding temperature and precipitation extremes as predictors in the Random Forest models, the explained global yield variance dropped by 43% for maize, 20% for soybeans, 27% for rice, and 18% for spring wheat (figure 1(b); supplementary table 3). For maize, soybeans and rice, the additional variance explained by the extreme indicators is larger than the variance that can be explained by mean climate indicators alone.

Climate extremes have a particularly strong association with maize yields at the continental scale; the explained variance in North America and Asia reduces by nearly 40% when extreme event indicators are excluded (figure 1(b)). Both regions together were responsible for more than 70% of global maize production in 1990–2008 (production shares shown in figure 4). Compared to mean growing season temperature and precipitation, extreme climate conditions also have a large influence on rice production in Asia (the explained variance decreased by 26% when excluding extreme event indicators, figures 1(a) and (b)), the most important rice producing continent with a 90% contribution to global production. Accounting for extreme conditions also more than doubles the explained variances of soy yields in North and South America (figures 1(a) and (b)), together responsible for more than 80% of global soy production.

4.3. Temperature-related indicators have highest predictive capacity for crop yields.

Overall, our analysis suggests that temperature-related predictors are more strongly correlated with crop yield anomalies than precipitation-related predictors across all four crops (see supplementary figure 9 for variable importance plots). Here, the relevance or predictive capacity of a predictor is quantified by the relative increase in MSE—calculated as out-of-sample error—between observed and predicted yield anomalies after randomly permuting the values of the predictor of interest (Methods).

For each crop, the top three predictor variables were among the following temperature-related variables: (i) warm day frequency (TX90p), (ii) cold night frequency (TN10p), (iii) the growing season average temperature, or (iv) the mean diurnal temperature range (supplementary figure 9). A greater diurnal temperature range indicates a wider temperature distribution at the hourly scale, characterised by high day-time temperatures and low night-time temperatures, both of which are shown to have negative yield effects (see next section).

While the number of frost days has low predictive capacity, we find that the indicator for cold night frequency has high variable importance for all crops except spring wheat. Frost events are defined by a fixed, absolute temperature threshold (New *et al* 2000) and may never occur in warm climate zones, or may generally not occur during the growing season in temperate regions, whereas the indicator for cold nights is percentile-based and depends on the temperature distribution of the given day of year at a particular location (Donat *et al* 2013b). Our results suggest that colder than usual temperatures reduce crop yields even above the frost-event threshold, because plant growth depends on accumulated temperature exposure (McMaster and Wilhelm 1997, Schlenker and Roberts 2009). Mean precipitation and SPI-6 play a less significant role for determining crop yield anomalies (with the exception of spring wheat in Oceania, supplementary figure 10 for variable importance plots by region). Similarly, the maximum 5-day precipitation intensity, which captures extremely intense precipitation events, has low variable importance across all crops (supplementary figure 9). Additionally, we tested the 1-day maximum rainfall intensity (Rx1day instead of Rx5day, with all other predictors being the same), resulting in equally low variable importance values for extreme precipitation at shorter time scales (not shown here).

4.4. Negative yield effects with increasing exposure to hot and cold temperature extremes

Random Forests do not rely on a prescribed functional relationship between predictors and the dependent variable, but represent a data-driven form that can be visualised by partial dependence plots (Methods). In the following and plots are provided for warm day frequency (TX90p) and cold night frequency (TN10p), i.e. two temperature predictors with highest predictive capacity.

We find negative impacts from increased warm day frequencies on all crops, i.e. an increase in numbers of unusually warm days is associated with decreases in yields (figure 2). Similar to the warm day frequency, higher frequencies of unusually cold daily minimum temperatures also have negative effects on yields of all crop types, except of spring wheat (figure 2). However, overall, the cold night frequency has low variable importance for spring wheat (see supplementary figure 9 for variable importance), hence the uncertainty of the functional shape is higher. At the regional scale, the effect of increased warm day frequency is particularly negative for maize in Europe

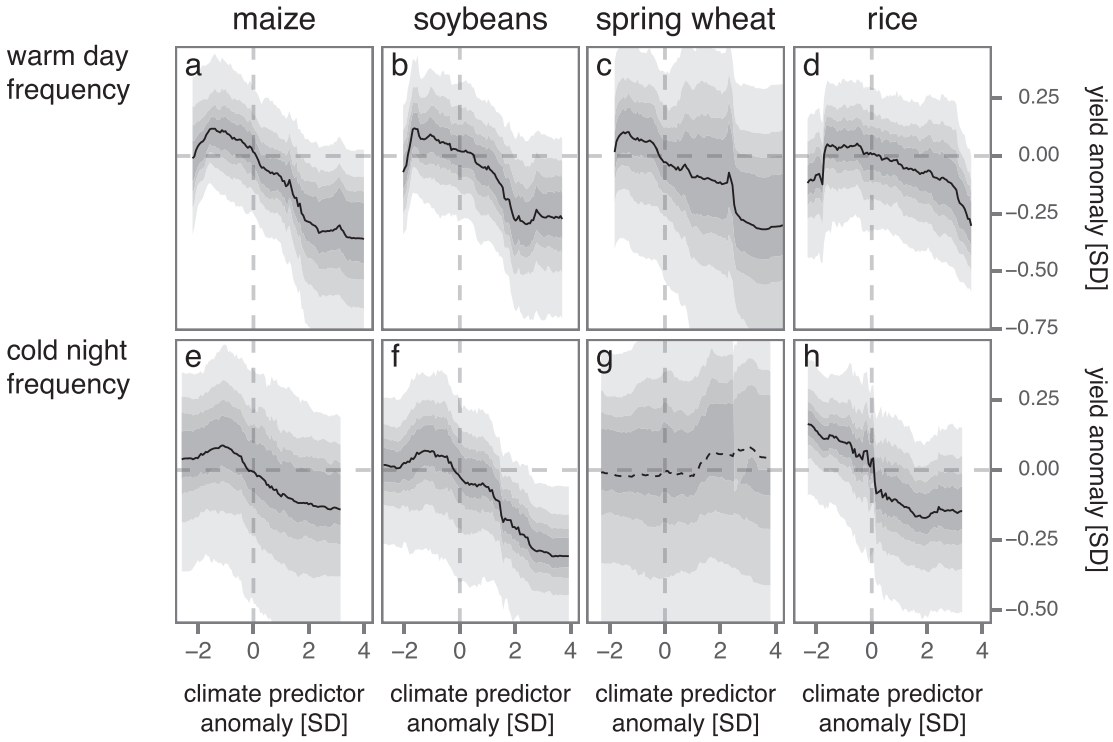

Figure 2. Partial dependence of standardised crop yield anomalies on exposure to unusually warm days (a)–(d) and exposure to unusually cold nights (e)–(h). Black lines: average effect on crop yields when the influence of all other predictors is accounted for. Positive values mean a positive effect on yield anomalies, negative values indicate a negative effect. Grey areas show the 95%, 85%, 75% and 66% uncertainty bands (Methods). The graph for spring wheat/cold night frequency is marked with a dash line, as this index has very low variable importance for this crop (see supplementary figure 9 for the variable importance).

and soybeans, spring wheat and rice in North America; increased occurrences of unusually cold days are negatively correlated with maize and soybean yields in Europe and rice yields in Oceania (supplementary figure 10 for regional variable importance plots).

4.5. Irrigation can mitigate parts of the effect of high temperature extremes

Guided by previous studies (Lobell *et al* 2013, Carter *et al* 2016)—which indicate that observed yield reductions associated with high temperatures may be induced by heat-related water scarcity—we tested whether the decline in yields with increasing warm day frequency is reduced by irrigation. We assessed the effect of irrigation on extreme event impacts by calculating the Random Forest for irrigated and rainfed grid cells separately (defined as $\geqslant$80% irrigated or rainfed, respectively) and visualising their partial dependences (Methods). We find that irrigation can mitigate negative yield impacts of high temperature extremes for maize, soybeans and spring wheat, with the greatest effects found for soybeans and spring wheat (figure 3). For soybeans, irrigation shifts the threshold above which temperatures have a negative impact to higher temperatures, while for maize and spring wheat, the response curve is flatter and the negative effect of high temperatures reduced. For rice, the fraction of rainfed cropping area is less than 10% globally, therefore, we omitted rice from this analysis.

4.6. Relevance of climate extremes for agricultural production particularly high for maize and spring wheat

Agricultural production is the product of yield (t/ha) and area harvested (ha), i.e. fluctuations in both variables have effects on fluctuations in crop production. We tested to which extent yield fluctuations due to variations in climate conditions and extreme events translate into production anomalies at the regional and global scale. By developing an aggregate indicator that takes into account a region's contribution to global production, the mean variability of production and the correlation between production anomalies and yield anomalies, we identify hot spot regions that are critical for food production and at the same time particularly susceptible to fluctuations in climate conditions, including climate extremes (Methods).

At the global scale, crop production anomalies are strongly correlated with fluctuations in yields. Correlation coefficients range between 0.78 and 0.94 (except for soybean production, which is dominated by fluctuations in harvested area) and inter-annual changes in yields explain ~60%–90% of the variance in production anomalies of spring wheat, maize and rice (figure 4; see table 2 for the numeric values). In combination with our previous results on the explained fraction of variance in yield anomalies (figure 1), we find that at the global scale, maize and spring wheat are the crops with the highest sensitivity of production to

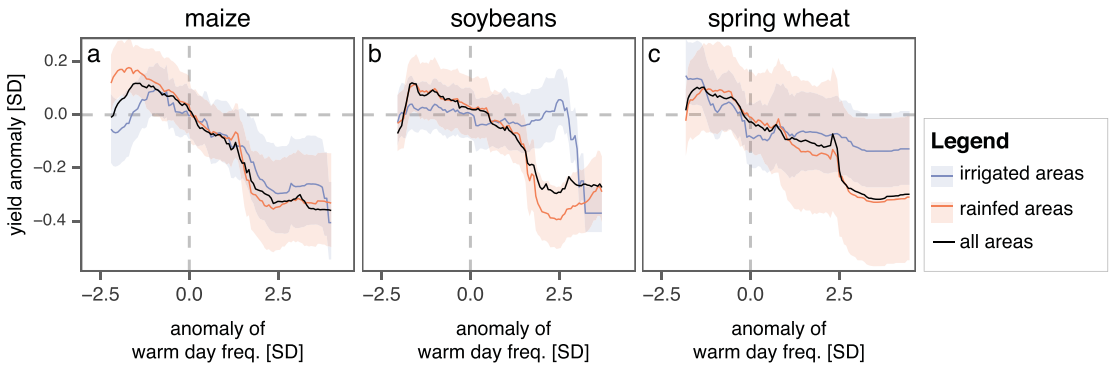

Figure 3. Effect of irrigation on functional relationship between warm day frequency and crop yields. Partial dependence of standardised crop yield anomalies on standardised anomalies of warm day frequency (TX90p), differentiated between irrigated and rainfed systems. Partial dependence plots are shown for (a) maize, (b) soybeans and (c) spring wheat. Blue areas and lines: irrigated cropping areas with irrigation fraction of greater than 80%. Orange areas and lines: rainfed cropping areas with irrigation fraction of less than 20%. Black lines: average marginal effect on crop yields of all cropping areas (irrigated, rainfed and mixed). The 50% uncertainty range (25th–75th percentiles) is added as shaded area.

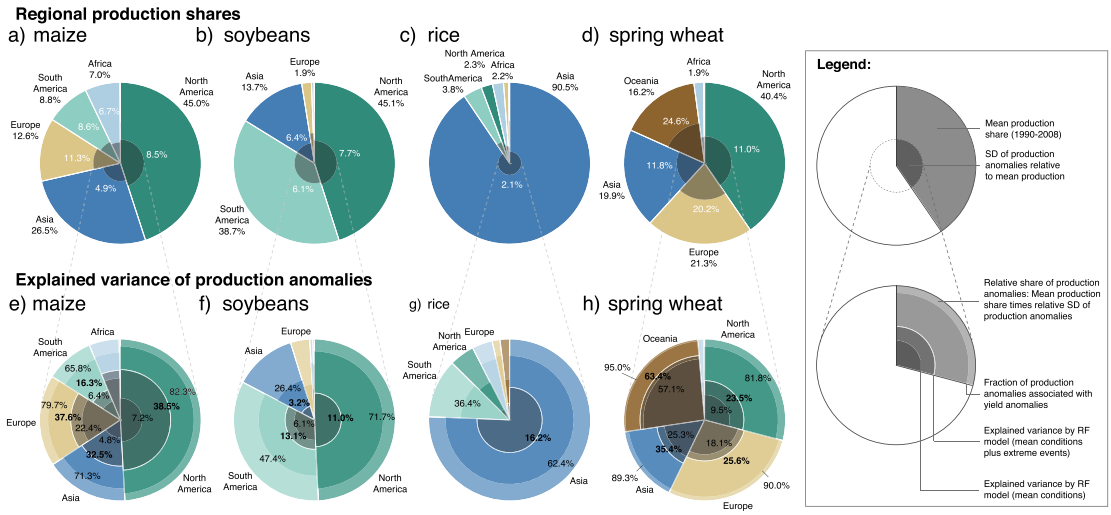

Figure 4. Explained yield variability in the context of global crop production. Top panel (a)–(d): slices represent the mean production share per continent (1990–2008); dark shaded inner circles: the standard deviation of production anomalies (after detrending) relative to mean production. Bottom panel (e)–(h): the size of each pie represents the share of production anomalies for every continent. The three inner circles represent (from outside to inside): (i) the fraction of variance of production anomalies that can be explained by yield anomalies, (ii) the fraction of variance of production anomalies explained by mean climate conditions plus extreme indicators (R^2 of full statistical model for yield anomalies multiplied with the factor (i); (iii) the fraction of variance of production anomalies explained by mean climate conditions (R^2 for reduced statistical model for yield anomalies multiplied with the factor i) (Methods).

climate variations and extremes, as they are characterised by a large variance of production anomalies, high correlation of production anomalies with yield fluctuations and a strong relationship between yields and climate conditions during the growing season (table 2).

Analysed separately by continent, the regions with highest contribution to global food production and at the same time high estimated sensitivity to climate conditions are: spring wheat production in Oceania, Europe, North America and Asia as well as maize production in North America and Europe (table 2, column for indicator A). Hotspot regions that show strong impacts of climate extremes include: North America for maize, spring wheat and soybeans production, Asia for rice and maize production and Europe for production of spring wheat (table 2, column for indicator B).

5. Discussion

In this study, we examined the historical and current impacts of climate extremes during the growing season on crop yields, using reported agricultural statistics at high spatial resolution. We used a non-parametric, nonlinear machine learning algorithm that allows for investigating these relationships without making assumptions about the functional shape of the effects. Our results underline the importance of considering impacts of climate extremes on the global food system and adapting agriculture to changes in extreme events

Table 2. Indicators ranking global and regional production by relevance for total crop production and sensitivity to climate fluctuations. Indicators i–iv: (i) share of a region's crop production relative to global production in 1990–2008 (%), (ii) mean variability of regional production (SD of anomalies relative to mean production, in %), (iii) the extent to which production anomalies are associated with yield anomalies (R^2 of regression between production anomalies calculated from yield anomalies versus actual production anomalies), (iv) the explained fraction of variance of yield anomalies, predicted by climate conditions (a—all climate factors, b—contribution of extreme events). Indicators A and B are the aggregate of indicators i, ii, iii and iv-a/iv-b (calculated as geometric mean). Numbers in bold highlight the six largest values in each column for all continent-crop combinations (without global values).

Crop	Continent	(i) Share of global production (%)	(ii) rel. SD of production anomalies (%)	(iii) R^2—production anomalies related to yield anomalies (%)	(iv-a) R^2—full statistical model (extreme events + mean conditions) (%)	(iv-b) R^2—contribution of climate extremes only (%)	Indicator A (i, ii, iii and iv-a) Production and total climate conditions (−)	Indicator B (i, ii, iii and iv-b) Production and climate extremes (−)
Maize	Global	100	4	72	49	43	35.0	33.8
Soybeans		100	4	24	20	20	20.9	20.9
Rice		100	2	60	28	27	24.2	23.9
Spring wheat		100	10	88	46	18	44.4	34.8
Maize	Africa	7	7	69	**55**	**16**	20.5	15.1
	Asia	**26**	5	71	**45**	**38**	25.4	**24.4**
	Europe	13	11	**80**	**47**	**19**	**27.0**	21.6
	South America	9	9	66	25	15	18.7	16.6
	North America	**45**	8	**82**	**47**	**38**	**34.8**	**33.1**
	Oceania	0	**25**	5	10	6	3.2	2.8
Soybeans	Africa	1	8	50	30	−1	9.1	—
	Asia	14	6	26	12	12	12.8	12.8
	Europe	2	**14**	19	6	2	7.5	5.6
	South America	**39**	6	47	28	**16**	23.7	20.4
	North America	**45**	8	72	15	15	24.8	**24.8**
	Oceania	0	**39**	46	1	0	2.9	1.0
Rice	Africa	2	5	59	3	3	6.3	6.3
	Asia	**91**	2	62	28	**26**	23.9	**23.5**
	Europe	1	4	64	6	6	6.2	6.2
	South America	4	8	36	5	4	8.3	8.0
	North America	2	6	27	3	−4	5.9	—
	Oceania	0	**27**	25	17	6	6.7	5.1
Spring wheat	Africa	2	10	21	1	1	4.2	4.1
	Asia	20	12	**89**	**40**	11	**30.2**	22.1
	Europe	21	**20**	**90**	28	8	**32.4**	**23.7**
	South America	0	7	37	0	−3	2.2	—
	North America	**40**	11	**82**	29	**17**	**32.0**	**28.1**
	Oceania	16	**25**	**95**	**67**	7	**39.9**	22.5

—to the extent it is possible—to meet future food demands. In the following paragraphs, we summarise and discuss the main results and outline potential applications and avenues for future research. A comprehensive discussion of the limitations of this study is included in SI section 2.

5.1. Yield variance explained by mean climate and climate extremes

Overall, we find that the climate factors considered in this study—capturing climate variability and climate extremes during the growing season—explain almost half of the variability in maize and spring wheat yield anomalies globally, and up to two third of the regional variability, e.g. for spring wheat in Oceania. We show that variables describing climate extremes contribute more than half of the explained variance of yield anomalies of maize, rice and soybeans and nearly half of spring wheat at the global scale, and hence are fundamental for understanding crop yield variations. The explained variances (R^2) presented here are of similar magnitude as previously reported in other studies: Lobell and Field (2007) and Ray *et al* (2015) estimate that growing season mean temperature and precipitation explain about one third of crop yield variations globally; Frieler *et al* (2017) determined the influence of weather variations on crop yields of main producers to be in the range of ~5% (rice in India) to ~80% (wheat in Australia). The reported values and findings are not directly comparable due to very different study designs and methods of calculating the explained variance. However, these studies agree that climate variations only explain a part of the yield variability and other factors, such as soil properties, management decisions (e.g. irrigation rate, fertiliser use) and market factors (e.g. fertiliser and energy prices) likely contribute to the remaining yield variations. To our knowledge, this study is the first to provide estimates of the fraction of variance of yield anomalies explained specifically by climate extremes. Unlike other previous studies, we report a conservative estimate of the explained variances by using a cross-validation approach and reporting R^2 values from out-of-sample predictions, and by applying one statistical model in one configuration for all crop types and regions.

5.2. Variable importance of temperature and precipitation for predicting yield anomalies

We identified the most influential predictors using a variable importance metric based on an increase in mean squared error, and found temperature-related predictors to be more relevant for yield predictions than precipitation-related climate factors (such as extreme precipitation or drought). The close link between temperature indicators, particularly high temperature indices, with yields is consistent with previous research at the national scale, which found heat waves to be significantly associated with grain yields (Lesk *et al* 2016, Zampieri *et al* 2017). In contrast, SPI-6—low values of which are indicative of meteorological drought—was found to be of low to medium importance for yield anomaly predictions, unlike previous studies that found a statistical relationship between reported droughts and yields at the national scale (Lesk *et al* 2016, Zampieri *et al* 2017). These differences in results suggest that (a) either droughts only influence yields if they occur at larger spatial and temporal scales than investigated here, or (b) meteorological droughts, defined by below-average precipitation over a given period, may not be sufficient to capture yield anomalies, and indicators measuring hydrological or agricultural drought (Keyantash and Dracup 2002, Passioura 2007, Quiring 2009) may be more suitable for predicting crop yield losses. Related to this, the relative contributions of temperature and precipitation anomalies to drought are difficult to disentangle—low rainfall and high temperatures both increase drought severity and are often significantly correlated (Trenberth and Shea 2005, Zscheischler and Seneviratne 2017). Previous research (Frieler *et al* 2017) as well as our results show that the negative yield effects of high temperatures are intertwined with water stress and can be mitigated by irrigation. We discuss the collinearity of predictors and our approach to address these in SI section 2.1. Here, we chose not to use a composite drought index that takes into account both temperature and precipitation to reduce collinearities in the predictor variables. However, future research could investigate the use of agricultural drought indicators that capture both precipitation and temperature effects, including the Standardised Precipitation-Evapotranspiration Index (SPEI) (Beguería *et al* 2014), or global gridded soil moisture datasets (e.g. Dorigo *et al* 2017) for predicting yield losses.

5.3. Critical production regions with high sensitivity to climate extremes

Adaptation to long-term climate change requires concerted efforts at local, regional and international level to ensure future food security. By using a composite indicator, this study identifies crop producing regions that exhibit a strong association with climate fluctuations and climate extremes and that are particularly critical for global production. These are primarily located in industrialised, high-input crop producing regions, such as North America and Europe. However, we emphasise that adaptation to climate extremes is critical not only in major crop producing countries, but also in regions with a population that highly depends on local agricultural production for their livelihoods and nutrition. As example, maize production in Africa has the second highest explained variance (R^2 of 54%, 15.8% contribution of extreme event indicators) of any of the crop/

continent combinations and hence a high dependence on climate conditions. While the share of global production is small (~7%), maize production is critical for the food security in the region—in Sub-Saharan Africa, the proportion of maize grain used directly for human consumption is approximately 70% compared to 3% in North America (Fischer *et al* 2014); hence any variations in crop production could have very severe impacts on the region's food supply. Such nuances could be further investigated by applying different weights to the individual indicators or by introducing additional indicators, such as the share of subsistence farming or the percentage of production for human consumption per region. Here, we aimed to capture influences of climate extremes on global production anomalies, and therefore calculated a composite index using equal weights, but a range of other combinations of indicators are possible and may be explored in future studies.

5.4. Adaptation to climate extremes

Climate change is expected to exacerbate the pressure on food production, as the frequency and severity of certain types of extremes, particularly high temperature extremes, are predicted to further increase in the future (Coumou and Robinson 2013, IPCC 2013, Sillmann *et al* 2013). Heat and frost extremes already pose a significant challenge to agricultural producers (Zheng *et al* 2012, Barlow *et al* 2015). Our results demonstrate that irrigation can partly mitigate the detrimental effects of extreme heat. However, freshwater availability is a concern under future climate conditions and previous research suggests that considerable areas of irrigated cropland worldwide may have to be converted to rainfed agriculture (Elliott *et al* 2014), increasing the vulnerability to high temperature extremes. Seasonal climate forecasts are an important adaptation tool that can assist farmers in assessing and potentially mitigating climate-related risks to crop production in the upcoming seasons (Hansen 2005, Ash *et al* 2007, Meza *et al* 2008, Hansen *et al* 2011). This study helps prioritising research efforts underpinning the development of such systems, by identifying the most relevant climate factors for yield predictions and estimating their contribution to yield fluctuations, for each region and crop individually. In future studies, the results may be extended to assess predictive skill several months prior to harvest and could be used to improve existing agricultural forecasts or support efforts to introduce such forecast systems in regions where they have not yet been implemented.

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