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In recent years, several extreme weather disasters have partially or completely damaged regional crop production[1–5]. While detailed regional accounts of the effects of extreme weather disasters exist, the global scale effects of droughts, floods and extreme temperature on crop production are yet to be quantified. Here we estimate for the first time, to our knowledge, national cereal production losses across the globe resulting from reported extreme weather disasters during 1964–2007. We show that droughts and extreme heat significantly reduced national cereal production by 9–10%, whereas our analysis could not identify an effect from floods and extreme cold in the national data. Analysing the underlying processes, we find that production losses due to droughts were associated with a reduction in both harvested area and yields, whereas extreme heat mainly decreased cereal yields. Furthermore, the results highlight ∼7% greater production damage from more recent droughts and 8–11% more damage in developed countries than in developing ones. Our findings may help to guide agricultural priorities in international disaster risk reduction and adaptation efforts.

In many regions of the world, there have been considerable changes in the nature of droughts, floods and extreme temperature events since the middle of the twentieth century[6–8]. Over agricultural areas, disasters arising from extreme weather can cause marked damage to crops and food system infrastructure, with the potential to destabilize food systems and threaten local to global food security. In recent years, nearly one-quarter of all damage and losses from climate-related disasters has been in the agricultural sector in developing countries[9]. With such disasters expected to become more common in the future[1,6,7], policymakers need robust scientific information to develop effective disaster risk management and adaptation interventions (for example, infrastructure, technology, management and insurance) to protect the most vulnerable populations and to ensure global food security.

Whether an extreme weather event results in a disaster depends not only on the severity of the event itself, but also on the vulnerability and exposure of the human and natural systems that experience it[6]. Past research has addressed agricultural effects of specific weather extremes with fixed definitions, such as degree days above some threshold[10–15]. This approach probably underestimates the crop effects of extreme weather disasters (EWDs), because similar extreme weather events may have differing effects depending on the vulnerability of the exposed system.

In this study, we address this bias by using a disaster data set compiled based on human impact. In addition, we attend to two further limitations of previous work on extreme weather and agriculture. First, several regional empirical studies have highlighted the adverse effects of extreme heat events on crop yields[10–13], and global modelling efforts have estimated future crop yield declines due to increasing extreme heat stress[14,15]. But this emphasis on crop yields offers an incomplete picture of crop production because of the potential for compensation or compounding of yield impacts by changes in harvested area[16]; and because crop production (and not yields)—together with access and utilization—determines food security[2,4,7,17,18]. Second, we seek to investigate the agricultural effects of often-overlooked extreme weather events, namely floods and extreme cold[2,3]. Thus, our study is the first, to our knowledge, that takes an empirical approach to estimating the influence of EWDs on crop area, yields and production at the global scale.

We use a statistical method, superposed epoch analysis[19] (also known as compositing, see Methods), to estimate average national per-disaster cereal production losses (Food and Agriculture Organization of the United Nations (FAO), http://faostat3.fao.org) across the globe due to reported droughts, floods and extreme temperature disasters from 1964 to 2007. Furthermore, we estimate the effects on cereal yield and harvested area separately to identify processes leading to production losses. On the basis of ∼2,800 reported extreme hydro-meteorological disasters collated by the Emergency Events Database (EM-DAT, http://www.emdat.be/database), we find that national cereal production during a drought was significantly reduced by 10.1% on average (95% confidence interval 9.9–10.2%), while years with extreme heat led to national production deficits of 9.1% (8.4–9.5%; Fig. 1a, b and Extended Data Table 1). These production deficits were equivalent to roughly 6 years of production growth; however, no significant lasting effects were noted in the years after the disasters. Estimated mean production losses were driven mainly by a preponderance of disasters with moderate effects on crops, as opposed to a few extreme cases (Extended Data Fig. 1), and were not strongly influenced by sample size (see Extended Data Fig. 2, Extended Data Table 2 and Supplementary Discussion).

During 1964–2007, these estimated EWD effects represent a loss of 1,820 million Mg due to droughts (approximately equal to the global maize and wheat production in 2013), and 1,190 million Mg due to extreme heat disasters (more than the global 2013 maize harvest). Over 2000–2007 (the period with the most complete disaster reporting compared with earlier decades), 6.2% of total global cereal production was lost due to EWDs relative to an estimated counterfactual global production without EWD effects (3.0% to extreme heat and 3.2% to drought).

Cereal yield declines during EWDs were 5.1% (4.9–5.2%) and 7.6% (7.0–8.1%) for drought and extreme heat, respectively (Fig. 2a). The harvested area dropped 4.1% (4.0–4.3%) during droughts, but was not significantly affected by extreme heat (Fig. 2b). This may be due to the shorter duration of extreme heat relative to droughts—while approximately one-third of droughts in this study spanned several years, all extreme heat disasters took place within a single year. Droughts may thus be more likely to last long enough to cause complete crop failure and discourage planting, while extreme heat disasters, especially outside key crop developmental stages, may affect crop growth and reduce yields without critically damaging harvests.

Our estimated yield deficits from EWDs cannot be directly compared to previous studies of the impact of seasonal mean climate trends over the same period[20] (see Supplementary Discussion). However, we derived a comparable measure to that reported previously[21], and estimated a yield sensitivity of 6–7% per 1 °C increase in seasonal mean

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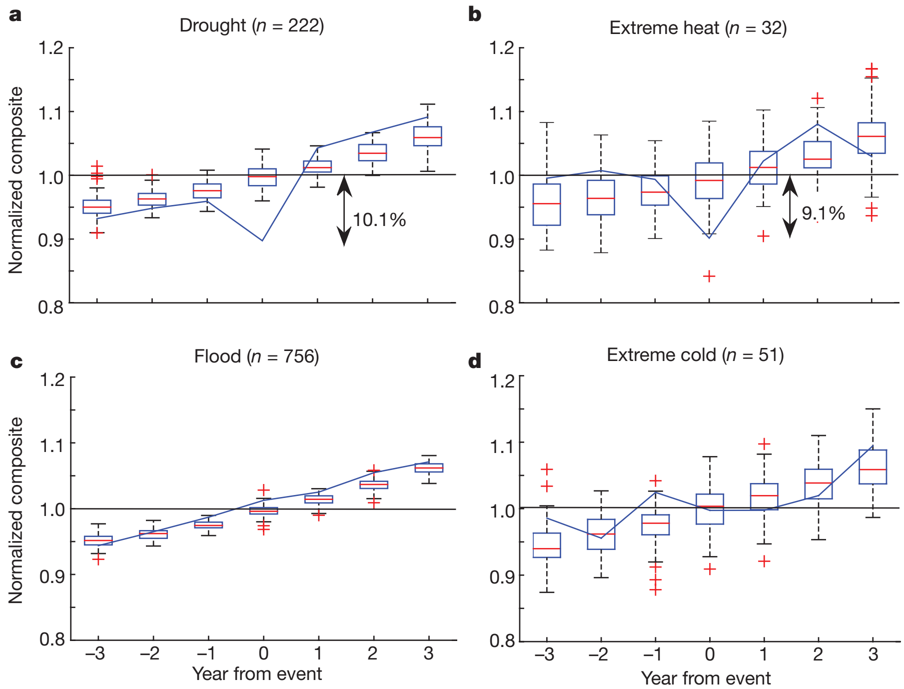

Figure 1 | Influence of EWDs on national cereal production. **a**–**d**, Normalized production composites for drought ($n = 222$) (**a**), extreme heat ($n = 32$) (**b**), flood ($n = 756$) (**c**) and extreme cold disasters ($n = 51$) (**d**) over 7-year windows centred on the disaster year (blue lines). Box plots depict the distributions of 1,000 false-disaster control composites, with red crosses denoting extreme outliers, and red dashes denoting medians. Production during drought and extreme heat years was 10.1% and 9.1% below the control mean, respectively, whereas no significant production signal was detected for floods or extreme cold. Production resumed normal levels immediately after drought and extreme heat. The increasing trend in production over the 7-year window reflects the observed growth trend.

weather associated with extreme heat disasters, which suggests that our observed extreme heat effects are not necessarily independent from those detected in studies examining changes in seasonal temperatures (Extended Data Fig. 3). Methodological differences and uncertainties prevent us from drawing strong conclusions based on this comparison. Our drought impacts, however, seem to be independent of previous estimates that used seasonal weather anomalies (see Supplementary Discussion).

Our results do not show significant production effects from extreme cold and floods (Fig. 1c, d). A potential explanation for this is that floods tend to occur in the spring in temperate regions as a result of snowmelt, and cold weather susceptibility in most agricultural regions is highest outside the growing season, which may render a sizeable portion of the flood and extreme cold disasters analysed in this study agriculturally irrelevant. The estimated lack of response may also be

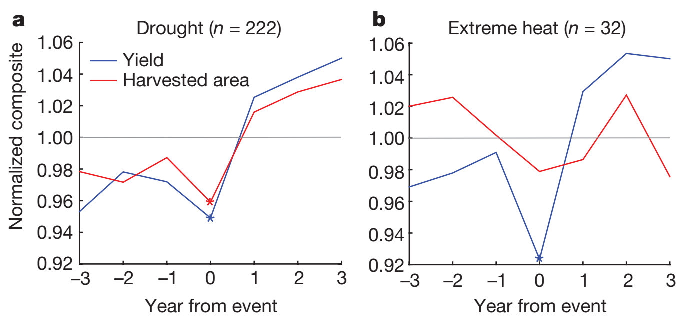

Figure 2 | Influence of EWDs on national cereal yields and harvested area. **a**, **b**, Yield (blue) and harvested area (red) composites for drought ($n = 222$) (**a**) and extreme heat ($n = 32$) (**b**), with significant points (those lying beyond the control box plot whiskers) marked by asterisks (box plots not shown for clarity). Drought was associated with significant deficits in both yield and harvested area (5.1 and 4.1%), whereas extreme heat revealed only significant yield impacts of 7.6% with no significant effect on harvested area.

an artefact of the spatial dimension of these disasters. While drought and extreme temperature affect broad regions, floods are a function of both weather and topography, and can be highly localized within a country[22]. Since this study uses country-level agricultural statistics, one may speculate that a more noticeable flood effect on sub-national production is masked at the national scale.

Several additional analyses offer more detailed insights into the effects of these EWDs on cereal production. Cereals in the more technically developed agricultural systems of North America, Europe and Australasia suffered most from droughts, facing on average a 19.9% production deficit compared to 12.1% in Asia, 9.2% in Africa, and no significant effect in Latin America and the Caribbean (overall difference in means $P = 0.02$; Fig. 3a and Extended Data Tables 3 and 4). This more severe production impact in the developed nations was driven by a substantial yield deficit of 15.9%, with no significant reduction in harvested area (Fig. 3b, c). We see three possible explanations for this pattern. First, it may arise from a tendency among lower-income countries to encompass diverse crops and management across many small fields, which may allow for some fields to resist drought better than others. This might reduce the national drought sensitivity compared to higher-income countries, where large-scale monocultures are more dominant. Second, lower-income countries may better resist drought because smallholders tend to use risk-minimizing strategies compared to the yield-maximizing ones prevalent in higher-income countries. Third, the pattern may relate to generally lower fair-weather yields in lower-income countries. In Asia, we found a significant reduction of 8.8% in harvested area during droughts with no corresponding yield deficit, suggesting that this region has a greater tendency for total crop failure in the event of a drought rather than harvesting with reduced yields[16]. The production effects in Africa did not correspond to significant deficits in either yield or harvested area.

While the production of all three crops was similarly affected by droughts (5–6% deficit each; Fig. 4a, Extended Data Tables 2 and 5), only maize was significantly affected by extreme heat (11.7% deficit, $P = 0.01$) (Fig. 4d). Maize was also the only crop with significant yield

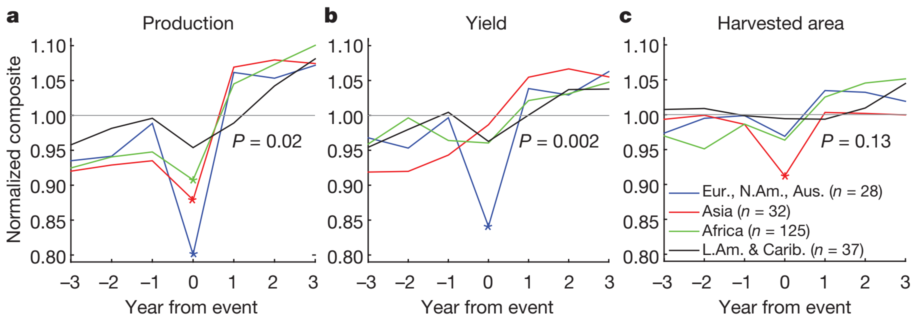

Figure 3 | A regional analysis of the influence of drought. a–c, Regional composites of production (**a**), yield (**b**) and harvested area (**c**) for drought, with significant points (those lying beyond the control box plot whiskers) marked by asterisks (box plots not shown for clarity). *P* values reflect significant differences between regions in drought-year response (Kruskal–Wallis test). The drought-year normalized production is 7.8% and 10.7% lower ($P=0.02$) in developed Western countries ($n=28$) than in Asia ($n=32$) and Africa ($n=125$) (**a**), a difference driven by a significantly greater yield deficit ($P=0.002$) (**b**). Meanwhile, the Latin America (L.Am) and Caribbean (Carib.) region ($n=37$) exhibits no significant response to drought. Aus., Australasia; Eur, Europe; N.Am., North America.

effects (12.4%, $P=0.002$) (Fig. 4b, e). We are hesitant to draw strong conclusions based on this difference, as it may be due to differing variance as well as mean (see Extended Data Table 6 and Supplementary Discussion). Furthermore, it may reflect the fact that maize is generally grown during summer months, which have the highest probabilities of extreme heat as defined in EM-DAT, while wheat is grown during the spring. Disaster data with monthly or daily resolution would enable us to investigate whether this apparent susceptibility of maize is a result of differing growing season.

Finally, more recent droughts (1985–2007) caused cereal production losses averaging 13.7%, greater than the estimated 6.7% during earlier droughts (1964–1984) ($P=0.008$, Fig. 5), which may be due to any combination of rising drought severity (although whether drought severity has increased globally is presently debated)[23–26], increasing vulnerability[6,27] and exposure to drought[6], and/or changing reporting dynamics (Extended Data Fig. 4). Sample size limitations prevented us from repeating a regional and temporal analysis for extreme heat.

Some limitations of our analyses are worth noting. First, we mainly focus on four principal types of EWDs, but follow-up studies should include tropical storms and extreme precipitation and wind events, especially since they may have an increasingly important effect on agriculture in the context of climate change[28]. Second, our estimates are biased towards more recent disasters as they are more abundantly reported in EM-DAT than older ones (see Extended Data Fig. 4 and Supplementary Discussion). Third, we use EWDs from the EM-DAT database, which collates disasters based on several criteria for substantial human impact (Methods). We may be underestimating the true effects of EWDs if disasters are included mainly based on urban impacts, or if extreme events occurring in sparsely populated areas are less likely to qualify as disasters. Finally, since we observe agricultural impacts at the national level, more notable local and regional effects of disasters may be muted (but conversely, finding a signal at the national level highlights the substantial influence of droughts and extreme heat). Future studies may arrive at a more detailed estimate by using subnational agricultural data, localizing the reported disasters within nations, selecting disasters taking place during the growing season, and controlling for severity of disasters. Linking the definitions of EWDs used in this study with statistical meteorological definitions will also enable a forecasting of future impacts.

Overall, there are four main conclusions from our study. First, over the period 1964–2007, drought and extreme heat substantially damaged national agricultural production across the globe. Within the framework of this study, no effect on agriculture was identified from floods and extreme cold. Second, drought reduced cereal yield and completely damaged crops, whereas extreme heat only affected yield, reflecting clear differences in the processes leading to overall production effects. Third, this study highlights an important temporal dimension to these impacts. While the damage to cereal production is considerable, this effect is only short term, as agricultural output rebounds and continues its growth trend after the disaster. Furthermore, we show that recent droughts had a larger effect on cereal production than earlier ones.

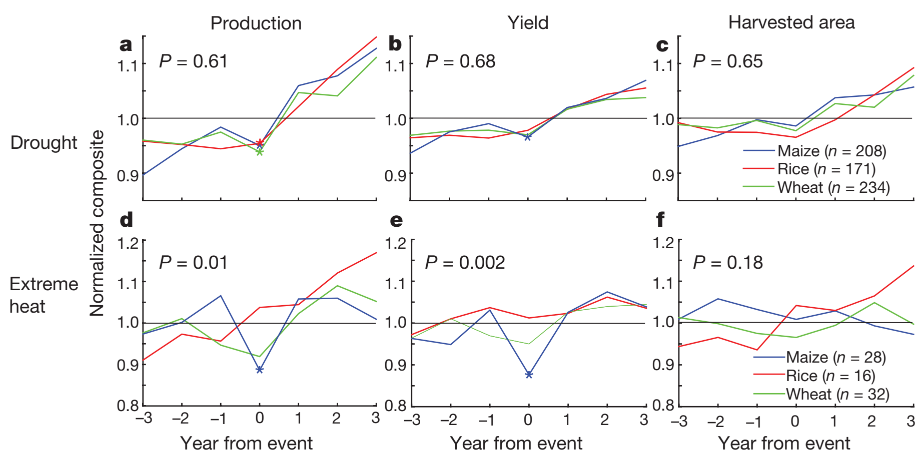

Figure 4 | The influence of drought and extreme heat on maize, rice and wheat. a–f, Drought and extreme heat composites of production (**a**, **d**), yield (**b**, **e**) and harvested area (**c**, **f**) for maize (blue), rice (red) and wheat (green), with significant points (those lying beyond the control box plot whiskers) marked by asterisks (box plots not shown for clarity). *P* values reflect significant differences between crops in disaster-year response (Kruskal–Wallis test). Maize production ($n=28$) responds more ($P=0.01$) to extreme heat than wheat ($n=32$) and rice ($n=16$), an effect driven by a substantial yield deficit ($P=0.002$). For drought data, maize ($n=208$), rice ($n=171$) and wheat ($n=234$).

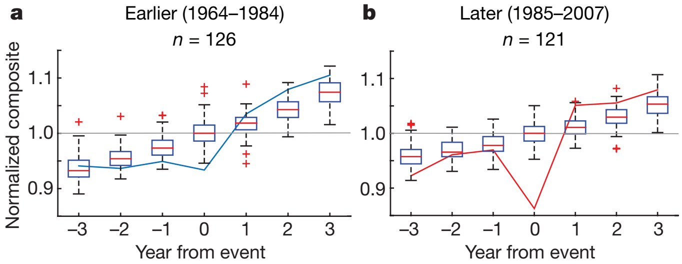

Figure 5 | A temporal analysis of the influence of drought.
a, **b**, Production composites for earlier (1964–1984, $n = 126$) (**a**) and later (1985–2007, $n = 121$) (**b**) droughts, with boxplots of 100 respective control composites. In later instances, mean drought-year production losses were greater (13.7%) than in earlier instances (6.7%; $P = 0.008$, Kruskal–Wallis test).

Finally, our regional and crop-specific analysis finds that developed nations suffer most from these EWDs.

Present climate projections suggest that extreme heat events will be increasingly common and severe in the future[1]. Droughts are likely to become more frequent in some regions, although considerable uncertainty persists in the projections[6]. This study, by highlighting the important historical effects of EWDs on agriculture, emphasizes the urgency with which the global cereal production system must adapt to extremes in a changing climate. Understanding the key processes leading to such crop losses enables an informed prioritization of disaster risk reduction and adaptation interventions to better protect the most vulnerable farming systems and the populations dependent on them.

Online Content Methods, along with any additional Extended Data display items and Source Data, are available in the online version of the paper; references unique to these sections appear only in the online paper.

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Supplementary Information is available in the online version of the paper.

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Author Contributions This research was designed and coordinated by N.R. All authors performed analyses, discussed the results, and wrote the manuscript.

Author Information Reprints and permissions information is available at www.nature.com/reprints. The authors declare no competing financial interests. Readers are welcome to comment on the online version of the paper. Correspondence and requests for materials should be addressed to N.R. (navin.ramankutty@ubc.ca).

METHODS

Superposed epoch analysis (SEA) is used to isolate an average EWD response signal using time series of national agricultural production data and EWDs. SEA is a statistical approach that has been used to enhance the signal (that is, influence of particular events) in time-series data, while reducing noise due to extraneous variables[19]. The EWDs are compiled from the Emergency Events Database (EM-DAT; http://www.emdat.be/database) and consist of 2,184 floods, 497 droughts, 138 extreme heat and 194 extreme cold disasters from 177 countries over the period 1964–2007. EM-DAT collects information on a reported disaster if at least ten people died, a state of emergency was declared, international assistance was called, or at least 100 people were injured, made homeless or required immediate assistance. Disaster reports are gathered from various organizations including United Nations agencies, governments, and the International Federation of Red Cross and Red Crescent Societies[8]. The agricultural data consist of country-level total production, average yield, and total harvested area data for 16 cereals (http://faostat3.fao.org) covering the 177 countries in the set of EWDs from 1961 to 2010.

From the time series of agricultural data, we extracted shorter sets of time series using a 7-year window centred on the year of occurrence of each EWD, with 3 years of data preceding and following each EWD. The data were normalized to the average of the 3 years preceding and following the event to remove the absolute magnitude of national data from the signal. For multi-year droughts, we averaged across all drought years to produce a single disaster year datum. For a 3-year drought, for example, the 7-year window became a 9-year window with seven data points (with the middle 3 years being averaged and assigned to year 0). The 7-year sets of EWD time series were then centred on the disaster year and averaged year-wise to yield single composited time-series of production, yield and harvested area for each EWD type (a total of 12 composited time series). The averaging thus strengthens the signal at the central year of EWD occurrence, while also cancelling the noise in the non-disaster years preceding and following the event.

During compositing, points on individual time series co-occurring with another disaster in the set were excluded from the mean. This procedure resulted in variable sample size across the 7 years of the composites. For brevity, we have presented mean sample sizes across all years; complete tabulated sample sizes are displayed in Extended Data Tables 2 and 4. Our composited mean estimate does not seem to be influenced by outliers (see Extended Data Fig. 1 and Supplementary Discussion). The signal-to-noise strength will certainly depend on the sample size, and we performed an analysis to estimate the influence of sample size (see Extended Data Tables 2 and 4, Extended Data Fig. 2 and Supplementary Discussion).

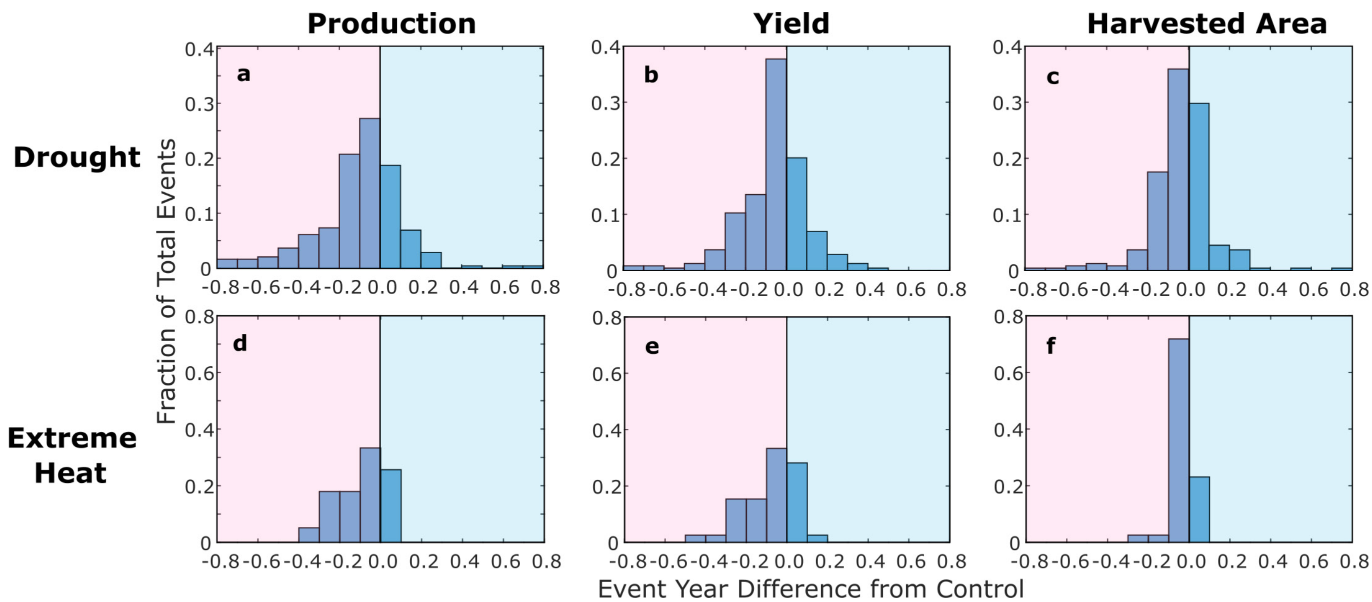
In addition to average per-disaster estimates, we also calculated aggregate production losses over specific time periods. For each extreme heat or drought, we first applied the average per-disaster percentage loss estimate (different values for extreme heat or drought) to the average national production across the six adjacent non-disaster years. We then computed the aggregate drought or heat-related global production loss for each year by summing the production losses for each disaster over the given time period. We estimated the percentage of global production lost to the EWDs relative to an estimated counterfactual global production in a world without EWDs (the latter being the sum of observed global production plus the estimated production loss).

The significance-testing procedure involved setting up a 'control' estimate by randomly resampling the agricultural data using sets of fictitious disasters with randomly generated years and countries of occurrence. The fictitious EWD time series were averaged as for the true ones to yield composited 'control' time series, and the entire process was repeated 1,000 times. We quantified EWD-year deficits in production, yield and harvested area by subtracting the true EWD time series from the mean of the controls. Excluding randomly generated disasters that happened to be real disasters systematically raised the impact estimates by $\sim$1%; to present a more conservative and rigorous detection of the disaster signal, we elected not to exclude such pseudo-disasters. Note that we chose not to de-trend the time series before compositing to remove technology-driven growth, but rather simply estimate the disaster signal as difference from control (see Fig. 1). We estimated the 95% confidence intervals for our point estimates of impacts using an approach similar to a delete-one jackknife resampling method (see Supplementary Discussion).

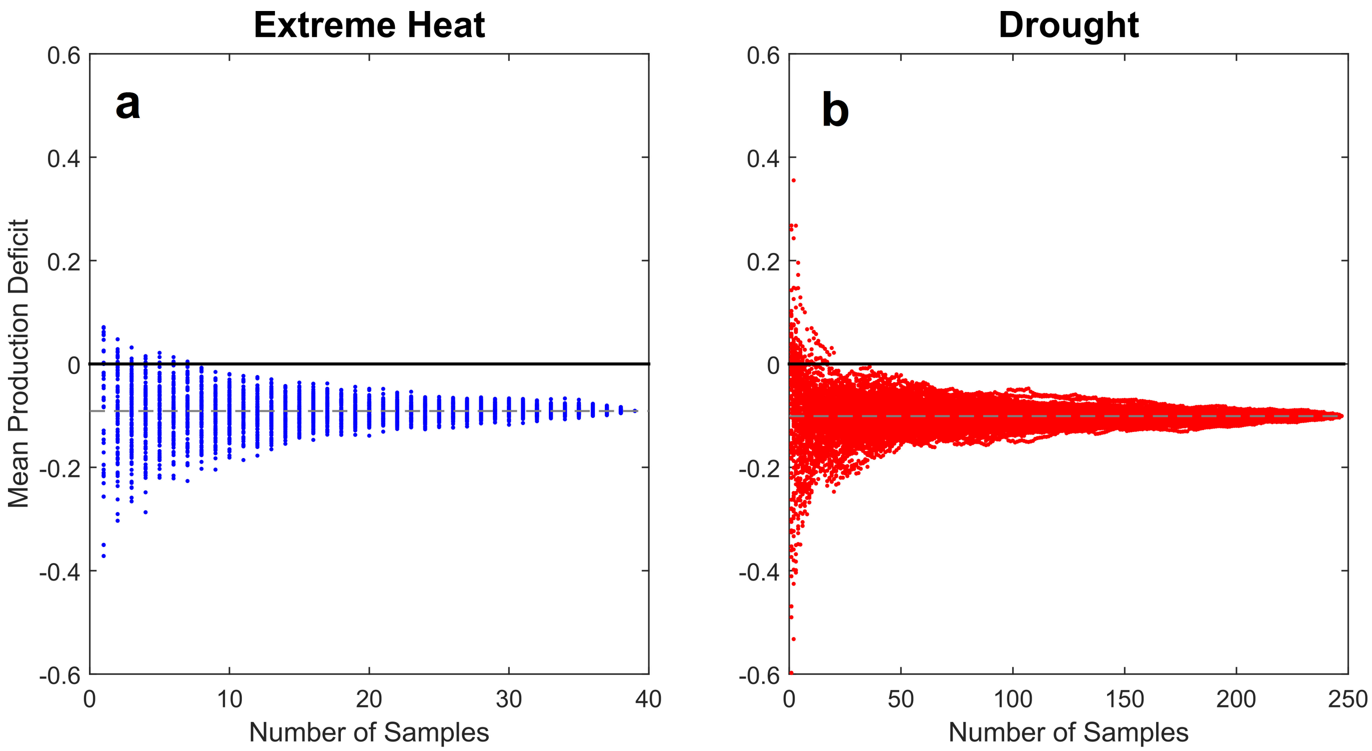
The percentage significance of each estimate of the EWD composites relative to control was estimated as the percentage of 1,000 control points less than the EWD composite estimate for each year. Points with estimated significance of $<$0.5% or $>$99.5% were considered significant deficits and surpluses, respectively, corresponding to a two-tailed 99% confidence level. While we chose a two-tailed approach for robustness, we found no significant surpluses. The significant points appear as asterisks in Figs 2–4, while for Figs 1 and 5 we present the EWD composites with the distribution of controls represented as an array of box-and-whisker plots for a visual representation of significance. The complete tabulated percentage significance values are presented in Extended Data Tables 1, 3 and 5.

The earlier-versus-later analysis for droughts was performed by applying the SEA procedure to the set of droughts divided roughly equally into earlier and later halves. Similarly, the regional analysis was conducted by repeating SEA for full set of disasters divided into four regional groupings, and the by-crop composites were obtained by repeating SEA on the full disaster sets using crop-specific agricultural data from the FAO (http://faostat3.fao.org). Statistical significance of differences between crop-specific, regional and earlier-versus-later composites was assessed using the Kruskal–Wallis test. We applied a quadratic transformation to the data for comparison to equalize variance between groups (verified using Levene's test), and used non-parametric tests when comparing groups as normal assumptions were not met (see Supplementary Discussion).

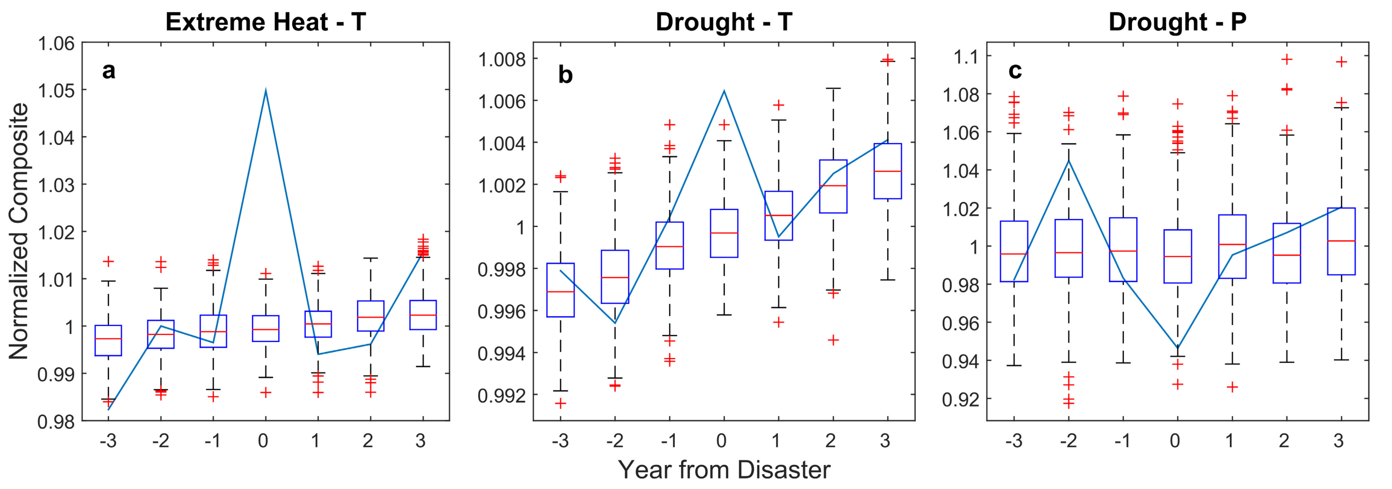
Code availability. All the core programs including codes to perform superposed epoch analysis and the various statistics described in this paper are available on Github (https://github.com/nramankutty/SEA-code).



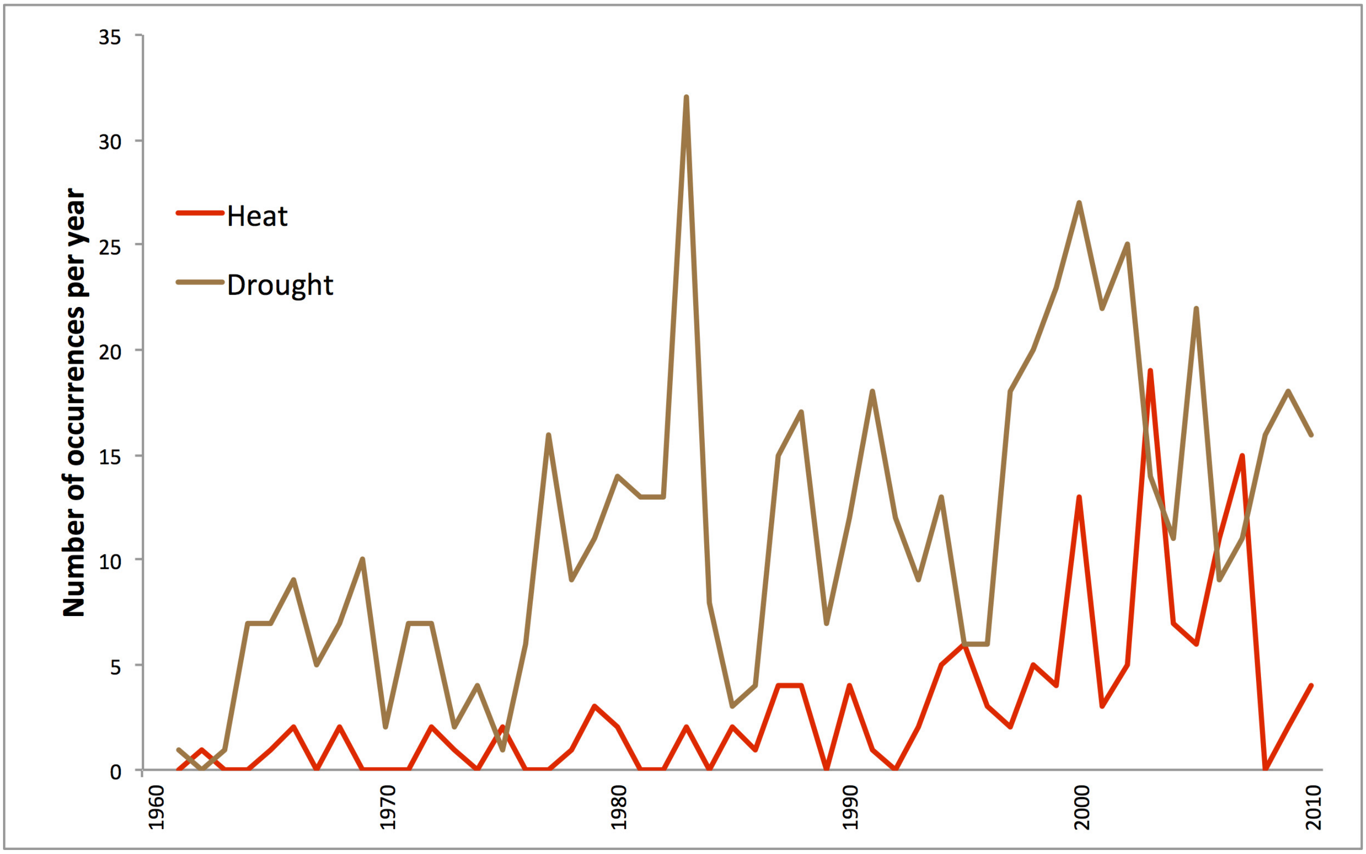
Extended Data Figure 1 | Distributions of individual responses to drought and extreme heat. a–f, Histograms of disaster-year differences from means of 1,000 resampled controls for drought ($n = 222$) (**a**–**c**) and extreme heat ($n = 32$) (**d**–**f**). A preponderance of moderately negative values (falling towards the right of the red shaded areas) underlies the negative mean disaster year signals, with a limited influence of extreme cases (those at the left of the red shaded areas).



Extended Data Figure 2 | The influence of sample size on estimated disaster effects. a, b, Estimated mean 16-cereal aggregated production deficit for extreme heat (**a**) and drought (**b**) in 200 sub-samples with size of (1, 2, …, *n*) (points). Dotted grey line shows the final estimated mean production deficit (9.1% for extreme heat, 10.1% for drought). Most of the initial variability at low sample sizes dissipates into the mean at well below the actual sample size ($n = 39$ for extreme heat, $n = 247$ for drought).



Extended Data Figure 3 | Seasonal weather anomalies of drought and extreme heat disasters in EM-DAT. a–c, Normalized composite mean growing season temperature for extreme heat ($n = 32$) (**a**) and drought ($n = 222$) (**b**), and total precipitation for drought (**c**). Box plots depict the distributions of 1,000 false-disaster control composites, with red crosses denoting extreme outliers and red dashes denoting medians. Years with extreme heat correspond to seasonal temperature anomalies of 1.2 °C, while drought years have only 0.15 °C warmer temperatures, with no significant precipitation anomaly.



Extended Data Figure 4 | Time series of the number of extreme heat and drought disasters per year from the EM-DAT database. The EM-DAT database is based on a compilation of disaster reports gathered from various organizations including United Nations agencies, governments and the International Federation of Red Cross and Red Crescent Societies. The time series of reported disasters per year exhibits an increasing trend, probably the result of more complete disaster reporting in more recent decades with a possible contribution from increasing disaster incidence. There is also large inter-annual variability in the number of disasters.

Extended Data Table 1 | Statistical significance of 16-cereal aggregate analysis

		Percent Significance (% of 1000 controls < disaster)						
	Year from Disaster	-3	-2	-1	0	1	2	3
Drought	Production	13.5	16.8	9.7	0	98.9	98.4	92.9
	Yield	22.0	71.0	8.9	0.0	93.3	86.3	68.7
	Harvested Area	21.5	7.3	35.2	0.0	92.4	95.3	87.5
Extreme Heat	Production	86.2	87.2	70.5	0.0	61.3	85.8	27.2
	Yield	62.1	56.5	59.8	0.1	81.9	82.7	60.5
	Harvested Area	84.2	91.2	68.9	22.1	25.1	70.6	9.8
Extreme Cold	Production	84.5	44.0	97.2	48.7	31.5	30.5	81.9
	Yield	41.4	18.9	97.2	50.2	60.7	57.8	94.8
	Harvested Area	90.1	69.3	81.0	53.2	19.1	17.5	47.9
Flood	Production	37.1	67.7	90.6	98.6	93.2	97.2	73.6
	Yield	57.1	65.0	29.5	93.1	85.1	98.3	96.2
	Harvested Area	26.6	61.6	97.3	95.7	85.9	75.0	30.6

Percentage of points on control composites less than EWD composites for 16-cereal aggregate, 1,000 control replicates total.

Extended Data Table 2 | Sample sizes for individual crop and 16-cereal aggregate analyses

		n =							
	Year from Disaster	-3	-2	-1	0	1	2	3	Mean
Drought	Wheat	139	129	144	146	132	122	123	134
	Rice	175	175	186	188	170	159	147	171
	Maize	205	207	225	231	206	196	183	208
Extreme Heat	Wheat	34	30	28	39	39	26	27	32
	Rice	18	14	15	19	17	16	14	16
	Maize	30	27	24	35	35	24	22	28
Drought	16-cereal aggregate	221	220	243	247	219	210	196	222
Extreme Heat	16-cereal aggregate	34	30	28	39	39	26	27	32
Extreme Cold	16-cereal aggregate	53	47	59	58	44	44	52	51
Flood	16-cereal aggregate	737	712	671	1345	625	602	603	756

Extended Data Table 3 | Statistical significance of regional analysis

		Percent Significance (% of 1000 controls < disaster)						
	Year from Disaster	-3	-2	-1	0	1	2	3
Production	Africa	23.1	24.1	11.4	0.0	93.8	96.0	92.1
	Asia	31.4	23.3	14.5	0.0	93.4	83.7	49.9
	North America, Europe, Australasia	27.8	18.9	61.4	0.0	96.3	80.9	82.2
	Latin America and Caribbean	48.2	65.0	74.0	7.6	24.2	65.4	75.4
Yield	Africa	16.4	85.7	3.6	0.7	88.0	86.2	88.4
	Asia	10.6	3.0	5.0	32.2	96.1	90.6	51.3
	North America, Europe, Australasia	73.9	18.2	71.8	0.0	85.7	40.8	68.0
	Latin America and Caribbean	42.4	71.2	90.2	2.1	24.3	75.7	38.6
Harvested Area	Africa	43.2	3.6	48.5	0.7	85.1	90.1	67.7
	Asia	64.2	70.3	49.0	0.0	60.6	49.5	38.8
	North America, Europe, Australasia	5.7	23.3	37.7	4.6	96.7	93.9	81.3
	Latin America and Caribbean	57.0	65.1	52.4	38.5	32.7	49.7	76.8

Percentage of points on control composites less than EWD composites for 16-cereal aggregate by region, 1,000 control replicates total.

Extended Data Table 4 | Sample sizes for regional analysis

	n =							
Year from Disaster	-3	-2	-1	0	1	2	3	Mean
North America, Europe, Australasia	28	27	25	34	27	26	30	28
Asia	39	31	35	36	28	31	23	32
Africa	117	120	144	139	129	117	110	125
Latin America and Caribbean	37	42	39	38	35	36	33	37

Extended Data Table 5 | Statistical significance of individual crop analysis

			Percent Significance (% of 1000 controls < disaster)						
		Year from Disaster	-3	-2	-1	0	1	2	3
Drought	Maize	Production	3.1	44.0	82.7	0.4	97.3	77.8	70.3
		Yield	7.5	73.1	76.9	0.1	59.6	53.9	72.1
		Harvested Area	7.1	24.3	84.3	19.5	97.4	80.0	54.6
	Rice	Production	53.1	27.5	1.1	0.1	45.1	94.8	96.4
		Yield	38.0	25.9	1.6	3.0	67.0	92.0	78.1
		Harvested Area	67.7	34.7	16.1	1.0	24.4	87.7	96.6
	Wheat	Production	64.9	34.6	49.0	0.2	94.4	54.2	89.4
		Yield	77.4	70.1	47.2	2.0	63.5	64.6	28.6
		Harvested Area	35.5	23.2	49.2	5.0	91.0	59.3	96.1
Extreme Heat	Maize	Production	70.1	81.2	95.8	0.2	72.7	44.3	6.8
		Yield	59.1	28.7	90.0	0.0	62.5	85.4	35.6
		Harvested Area	67.4	93.7	81.8	52.8	64.7	18.0	7.5
	Rice	Production	29.1	62.5	39.3	77.4	68.5	86.2	80.0
		Yield	51.1	78.2	90.1	62.2	60.5	82.6	38.5
		Harvested Area	26.1	35.8	14.9	80.4	66.9	78.6	86.4
	Wheat	Production	63.6	83.0	25.9	2.3	57.9	83.1	35.9
		Yield	60.5	90.8	34.1	4.4	75.6	63.7	49.3
		Harvested Area	64.6	51.9	28.8	10.3	35.4	79.4	25.0

Percentage of points on control composites less than EWD composites for individual crop analysis, 1,000 control replicates total.

Extended Data Table 6 | Kruskal–Wallis assumptions test results for group comparison analyses

Analysis	Figure	Data	Normal? (Anderson-Darling test)	Equal variance? (Levene's Absolute test)
Regional	3a	Production	No	Yes
	3b	Yield	No	Yes
	3c	Harvested Area	No	Yes
Individual Crop: Drought	4a	Production	No	Yes
	4c	Yield	No	Yes
	4e	Harvested Area	No	Yes
Individual Crop: Extreme Heat	4b	Production	No	Yes
	4d	Yield	No	No
	4f	Harvested Area	No	No
Earlier-Later Droughts	5	Production	No	Yes