Letter

Changing risks of simultaneous global breadbasket failure

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The risk of extreme climatic conditions leading to unusually low global agricultural production is exacerbated if more than one global 'breadbasket' is exposed at the same time. Such shocks can pose a risk to the global food system amplifying threats to food security and could potentially trigger other systemic risks[1,2]. So far, while the possibility of climatic extremes hitting more than one breadbasket has been postulated[3,4] little is known about the actual risk. Here we combine region-specific data on agricultural production with spatial statistics of climatic extremes to quantify the changing risk of low production for the major food producing regions ('breadbaskets') over time. We show an increasing risk of simultaneous failure of wheat, maize and soybean crops, across the breadbaskets analyzed. For rice, risks of simultaneous adverse climate conditions have decreased in the recent past mostly owing to solar radiation changes favoring rice growth. Depending on the correlation structure between the breadbaskets, spatial dependence between climatic extremes globally can mitigate or aggravate the risks for the global food production. Our analysis can provide the basis for more efficient allocation of resources to contingency plans and/or strategic crop reserves that would enhance the resilience of the global food system.

Climate variability explains at least 30% of year-to-year fluctuations in agricultural yield[5]. Under 'normal' climatic circumstances the global food system can compensate local crop losses through grain storage and trade[6]. However, it is doubtful whether the global food system is resilient to more extreme climatic conditions[7], when export restrictions[8] and diminished grain stocks may undermine liquidity in agricultural commodity markets, resulting in higher price volatility. The food price crisis in 2007/08 has shown that climatic shocks to agricultural production contribute to food price spikes[9] and famine[10], with the potential to trigger other systemic risks including political unrest[1] and migration[2]. Climatic teleconnections between global phenomena such as El Niño Southern Oscillation (ENSO) and regional climate extremes such as Indian heatwaves[11] or flood risks around the globe[12] could lead to simultaneous crop failure in different regions[13], therefore posing a risk to the global food system[6,8], and amplifying threats to global food security. While the possibility of a climatic extreme hitting more than one breadbasket has been a growing cause for concern[3,4], only few studies have investigated the probability of simultaneous production shocks [14–16] or estimated the joint likelihoods of adverse climate conditions[17]. Here we present quantitative risk estimates of simultaneous breadbasket failures due to climatic extremes by explicitly accounting for spatial dependence structures between the regions and show how risk has changed over time.

We analyzed climatic and crop yield data (see Methods) for the main agricultural regions within the highest crop producing countries by mass both in 1961 and 2012, according to FAO data, i.e. United States, Argentina, Europe, Russia/Ukraine, China, India, Australia, Indonesia and Brazil. The global breadbaskets for each crop and corresponding states and provinces are shown in Supplementary Fig. SF1. For wheat, maize, soybean and rice the selected breadbaskets account for 74%, 74%, 81% and 74% of the total production in the breadbasket countries and 56%, 56%, 73% and 38% of the total global production in 2012, respectively. We developed region-dependent relationships between climatic variables (temperature, precipitation and solar radiation indicators; summarized in Supplementary Table ST1) and logistically de-trended crop yields using data for the period 1967 to 2012 and analyzed the dependence structure at regional and global scales using a Vine copula approach (see Methods). We report results (i) for each breadbasket, and the states/provinces within that breadbasket and (ii) aggregating across multiple breadbaskets at a global scale. We look at changes over time by comparing the period 1967-1990 with 1991-2012. For the individual breadbaskets, increases of climate risk (defined as exceedance of a region-specific climate threshold that corresponds to the lower 25% yield deviation percentile, see Supplementary Fig. SF3) and simultaneous crop failures of states/provinces within one breadbasket were found for 18 out of 32 climate indicators across all regions and crops. For example, for soybean in China, the critical climate indicator is the number of days above 30°C during the growing season (see Supplementary Table ST1). While only 1.2% of extreme hot months occurred simultaneously in all provinces of the Chinese soybean breadbasket in any given year in the period 1967-1990 (defined as the exceedance of the "days-above-30°C" temperature indicator threshold), this increased to 18.4%for the period 1991-2012 (Fig. 1). This accords with other analysis[18,19] that reports a significant increase in temperature extremes in China in recent decades.

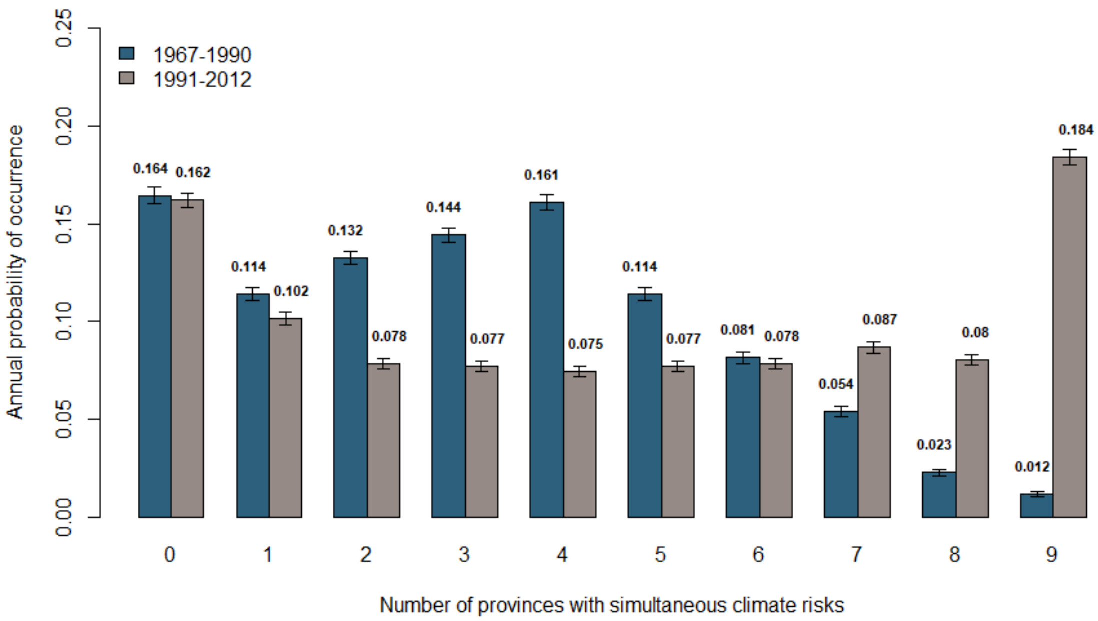

Figure 1: Likelihood of simultaneous climate risks in the 9 most important soybean producing provinces in China threatening agricultural production: Defined as relevant climate indicators exceeding the value that corresponds to the lower 25% yield deviation percentile. The error bars indicate the standard error based on bootstrapping (Methods).

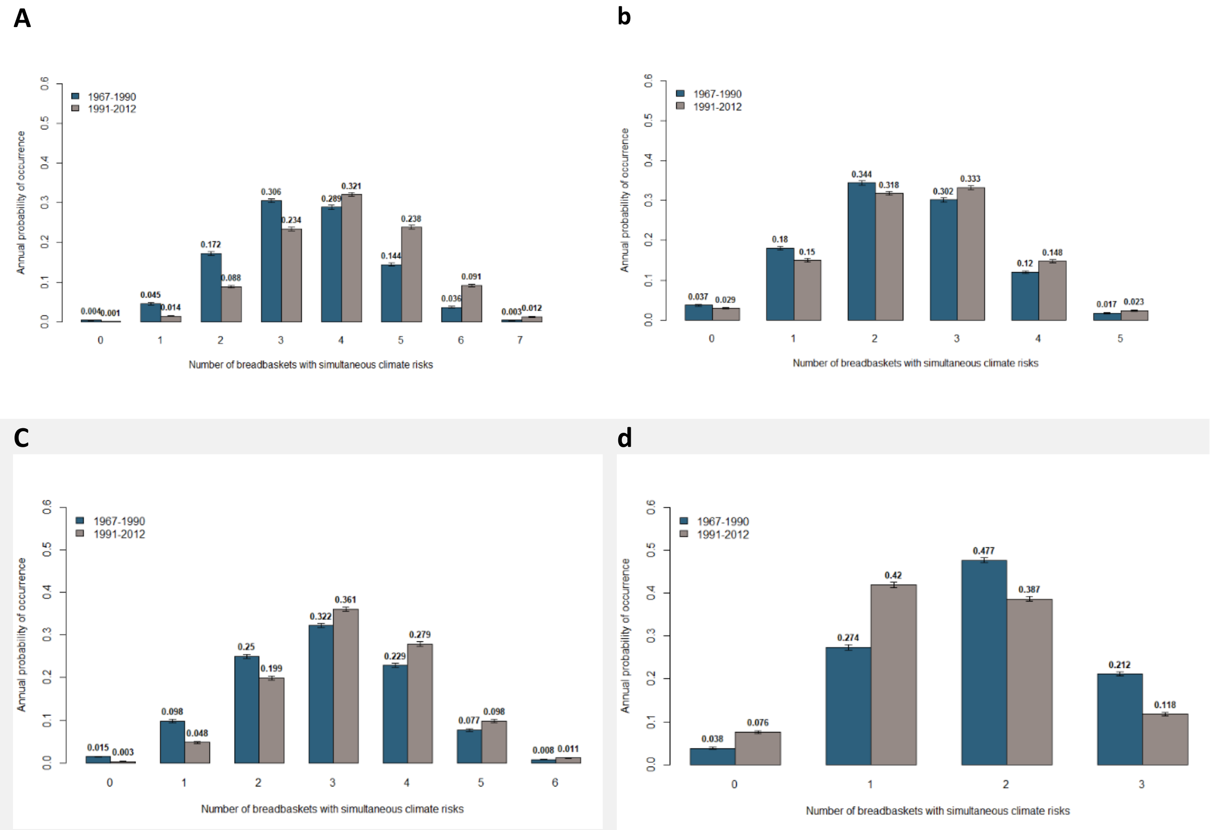

Figure 2: Likelihood of climatic conditions simultaneously threatening crop losses in the global breadbaskets: Defined as relevant climate indicators exceeding the value that corresponds to the to the lower 25% yield deviation percentile. (A) wheat (b) soybean (c) maize and (d) rice breadbaskets.

On a global scale, there has been a significant increase in probability of multiple global breadbasket failures for all crops except for rice (Figure 2). The number of breadbaskets suffering from unfavorable climate for plant growth increased significantly on average between the two periods for wheat, maize and soybean and decreased for rice. Looking at the extremes, the annual probability of all breadbaskets experiencing climate risks simultaneously increased from 0.3 to 1.2% for wheat, from 0.8 to 1.1% for maize and from 1.7 to 2% for soybean. For rice, it decreased from 21.2 to 11.8% between the two periods. Wheat has experienced the largest increases in simultaneous climate risks (16.8% from in average 3.42 to 4 breadbaskets experiencing risks simultaneously). Risks from temperature effects have increased in all temperature sensitive wheat breadbaskets, whereas precipitation risks have only increased in India and Australia and decreased in China, Europe, Russia/Ukraine and USA (see Supplementary Figures SF4 and SF5). For the summer crops soybean and maize, simultaneous risks have on average increased by 6.5% and 9.9% respectively. Climate risks have decreased in the Americas (except for precipitation affecting soybean in Argentina) and increased in Asia and Europe (except for precipitation based risks affecting maize in China). In general, the risks of extreme temperature simultaneously hitting yield in multiple breadbaskets have increased more than risks of unfavorable precipitation (see Supplementary Figures SF5).

Although precipitation and temperature are usually seen as the most important climate factors influencing crop yields in statistical models[5,20], precipitation often has no substantial impact on rice production as rice is mostly irrigated[21–23]. Moreover, there is no discernable temperature effect in Indonesia because temperatures are generally below the critical thresholds during rice growing season[24]. In China, temperature effects depend largely on the region[25] and no single clear indicator was found for the entire rice breadbasket. Consideration of solar radiation helps to explain more of the variation in rice production. Risks from extreme solar radiation decreased in all three rice breadbaskets and the overall likelihood of simultaneous climate risks in the global rice breadbaskets decreased by 17%. A detailed description of changes in rice climate risks and possible explanations can be found in the Methods section. Note that our approach of estimating the number of breadbaskets experiencing simultaneous climatic risks does not account for the different sizes of the breadbaskets, for instance the maize production being one order of magnitude higher in the US breadbasket than in the Argentinian one. To give an impression of the magnitude of those simultaneous risks we show in Supplementary Figure SF 6 the distribution of area simultaneously affected by climate risks in the global breadbaskets which shows that the changes in simultaneous risks are robust, even if the breadbaskets where weighted by area

For soybean, the implications for production of breadbasket failures in all five breadbaskets (which are associated with climate risks) would be at least 12.55 million tons of crop losses (with crop losses defined as the 25 percentile detrended yields multiplied by 2012 harvested area, see calculations in Supplementary Table Expected_loss_calculations), which exceeds the 7.2 million ton losses in 1988/89, one of the largest historical soybean production shocks[4]. Simultaneous maize, wheat and rice climate risks in all of the breadbaskets considered here would lead to production losses of at least 25.9, 18.8 and 0.5 million tons respectively. For comparison, the largest global shocks (defined as total production anomalies) that have occurred in the past were estimated at 55.9 million tons in 1988 for maize , 36.6 million tons in 2003 for wheat and 22 million tons in 2002 for rice due to a failure of monsoon[4] .

The aggregate risk of low production at a global scale is influenced by the spatial dependence in climate variables between breadbaskets, as well as by the climate risk in each breadbasket. There are positive as well as negative spatial dependencies between the relevant climatic variables, so the aggregate expected agricultural production losses from simultaneous climate risks in all breadbaskets can be both higher and lower than would be the case were relevant climate variables in different breadbaskets to be statistically independent. However, we found no significant change in the spatial dependence structure between the two periods. The changes to simultaneous climate risks that are reported above are attributable to changes in climatic mean and variance only – no significant change was detectable in the spatial dependence structure between the breadbaskets.

We compared the case of statistical independence between breadbaskets with the observed climate data, to show the effect of spatial dependence in climate variables (see Supplementary Fig. SF7). The spatial dependence in climatic variables is shown to increase the aggregate risk of production losses in some cases e.g. the expected loss (for details on the calculations see Supplementary Information Expected_loss_calculations) for rice in the second period is slightly higher than in the independent case. In other cases, spatial dependence mitigates the aggregate risk (i.e. the losses are negatively correlated), as is the case for soybean, maize, wheat and for rice in the first period.

Overlaying inter-dependent climate risks with global trade patterns[26], we estimated the significance of climatic dependence between breadbaskets on the global food system. A positive correlation between maximum temperature in the EU and in Australia, for example, (a full list of correlation matrices can be found in Supplementary Figure SF8) indicates that increasing temperature risks in Australia, an important wheat exporter to the EU, puts additional pressure on the EU in the case of a drought during the wheat growing season. Precipitation based risks for soybean in India and Argentina, on the other hand, are negatively correlated which means that soybean losses in India can be mitigated by imports from Argentina. For maize, mean temperature in the EU during growing season is positively correlated with growing season precipitation in Brazil, a net maize importer to the EU. If Europe experiences an extremely hot year, Brazil is likely to get enough rainfall for its maize production and is able to mitigate losses in the EU through trade. This is especially important as in the last decades, precipitation risks in Brazil have declined whereas temperature-based risks in the EU have increased (see Supplementary Figure SF5).

Analysis of climatic risks to crop production has conventionally used crop models on a global scale[27]. Whilst crop-models can incorporate complex time-dependent climatic influences on yield, there is a mismatch between model predictions and actual yield data[27,28]. The more direct approach that we have adopted has incorporated phenological as well as statistical information, with a specific focus upon the climatic factors that demonstrably influence low agricultural production. Whilst statistical analysis of global production data does not identify significant inter-regional spatial dependence or climate-related change signals, because of the number of confounding factors, we have been able to fingerprint the effects of these signals through direct analysis of the relevant climatic data. We have therefore been able to begin to interpret the risks of multiple simultaneous climate extremes to crop production. Climate risks to wheat, maize and soybean production in the global breadbaskets have changed already. Climate risks to the rice breadbaskets have decreased over past decades, though studies indicate this trend may change direction in the future[24,29,30]. Whilst our empirically based approach has some attractions compared to global crop modelling, there were inevitable limitations. Our study only considered temperature, precipitation and, for rice, solar radiation data. However, there are numerous other factors that could influence the climate-yield relationship, e.g. we did not consider wind speed, ozone exposure or CO_2 effects[31,32]. Owing to limited data availability, we could not consider agronomic factors such as irrigation, pest infestation or different crop varieties. This study represents a first empirical analysis of global and regional dependence structures of climate risks in the global breadbaskets. Further analysis of underlying teleconnection patterns is needed to understand how dependence structures might change in the future.

Quantifying likelihoods of simultaneous climate risks as in our approach should help governments, businesses and international institutions to identify plausible risk scenarios and allocate proportional resources to contingency plans and/or strategic crop reserves. Importantly, as demonstrated here, not only overall risks may change over time, but the likely combinations of conditions that threaten the food system may also have changed. For trade networks, which are established over time, such changes may threaten food security when existing trade connections are not able to buffer simultaneous breadbasket failures. Our identification of climatic patterns associated with global crop losses can help to target the deployment of early warning systems.

References

1. Johnstone, S. & Mazo, J. Global warming and the Arab Spring. *Survival* **53**, 11–17 (2011).
2. Von Braun, J. & Tadesse, G. Global food price volatility and spikes: an overview of costs, causes, and solutions. *ZEF-Discuss. Pap. Dev. Policy* (2012).

3. Schaffnit-Chatterjee, C., Schneider, S., Peter, M. & Mayer, T. Risk management in agriculture. *Dtsch. Bank Reseach Sept* (2010).
4. Bailey, R. & Benton, T. Extreme weather and resilience of the global food system. Final Project Report from the UK-US Taskforce on Extreme Weather and Global Food System Resilience, The Global Food Security programme, UK. (2015).
5. Lobell, D. B. & Field, C. B. Global scale climate–crop yield relationships and the impacts of recent warming. *Environ. Res. Lett.* **2**, 014002 (2007).
6. Bren d'Amour, C., Wenz, L., Kalkuhl, M., Christoph Steckel, J. & Creutzig, F. Teleconnected food supply shocks. *Environ. Res. Lett.* **11**, 035007 (2016).
7. Fraser, E. D. G., Simelton, E., Termansen, M., Gosling, S. N. & South, A. "Vulnerability hotspots": Integrating socio-economic and hydrological models to identify where cereal production may decline in the future due to climate change induced drought. *Agric. For. Meteorol.* **170**, 195–205 (2013).
8. Puma, M. J., Bose, S., Chon, S. Y. & Cook, B. I. Assessing the evolving fragility of the global food system. *Environ. Res. Lett.* **10**, 024007 (2015).
9. Von Braun, J. The food crisis isn't over. *Nature* **456**, 701–701 (2008).
10. Maxwell, D. & Fitzpatrick, M. The 2011 Somalia famine: Context, causes, and complications. *Glob. Food Secur.* **1**, 5–12 (2012).
11. Ratnam, J. V., Behera, S. K., Ratna, S. B., Rajeevan, M. & Yamagata, T. Anatomy of Indian heatwaves. *Sci. Rep.* **6**, (2016).
12. Ward, P. J. *et al.* Strong influence of El Niño Southern Oscillation on flood risk around the world. *Proc. Natl. Acad. Sci.* **111**, 15659–15664 (2014).
13. Anderson, W. B., Seager, R., Baethgen, W., Cane, M. & You, L. Synchronous crop failures and climate-forced production variability. *Sci. Adv.* **5**, eaaw1976 (2019).
14. Tigchelaar, M., Battisti, D. S., Naylor, R. L. & Ray, D. K. Future warming increases probability of globally synchronized maize production shocks. *Proc. Natl. Acad. Sci.* 201718031 (2018).
15. Mehrabi, Z. & Ramankutty, N. Synchronized failure of global crop production. *Nat. Ecol. Evol.* **3**, 780 (2019).
16. Gaupp, F., Pflug, G., Hochrainer-Stigler, S., Hall, J. & Dadson, S. Dependency of Crop Production between Global Breadbaskets: A Copula Approach for the Assessment of Global and Regional Risk Pools. *Risk Anal.* (2016).
17. Sarhadi, A., Ausín, M. C., Wiper, M. P., Touma, D. & Diffenbaugh, N. S. Multidimensional risk in a nonstationary climate: Joint probability of increasingly severe warm and dry conditions. *Sci. Adv.* **4**, eaau3487 (2018).
18. Zheng, H. F. *et al.* Phosphorus control as an effective strategy to adapt soybean to drought at the reproductive stage: evidence from field experiments across northeast China. *Soil Use Manag.* **31**, 19–28 (2015).
19. Yin, X. G., Olesen, J. E., Wang, M., öZtüRk, I. & Chen, F. Climate effects on crop yields in the Northeast Farming Region of China during 1961–2010. *J. Agric. Sci.* **154**, 1190–1208 (2016).
20. Lobell, D. B., Schlenker, W. & Costa-Roberts, J. Climate trends and global crop production since 1980. *Science* **333**, 616–620 (2011).
21. Duncan, J. M. A., Dash, J., Tompkins, E. L., 1 UWA School of Agriculture and Environment, University of Western Australia, Perth, WA, 6009, Australia & 2 Geography and Environment, University of Southampton, Southampton, Hants, UK, SO171BJ. Observing adaptive capacity in Indian rice production systems. *AIMS Agric. Food* **2**, 165–182 (2017).

22. Fishman, R. M. Climate change, rainfall variability, and adaptation through irrigation: Evidence from Indian agriculture. *Job Mark. Pap.* (2011).
23. Tao, F., Yokozawa, M., Liu, J. & Zhang, Z. Climate-crop yield relationships at provincial scales in China and the impacts of recent climate trends. *Clim. Res.* **38**, 83–94 (2008).
24. Wassmann, R. *et al.* Regional vulnerability of climate change impacts on Asian rice production and scope for adaptation. *Adv. Agron.* **102**, 91–133 (2009).
25. Zhang, T., Zhu, J. & Wassmann, R. Responses of rice yields to recent climate change in China: An empirical assessment based on long-term observations at different spatial scales (1981–2005). *Agric. For. Meteorol.* **150**, 1128–1137 (2010).
26. Chatham House. 'resourcetrade.earth' 2012 data. (2017).
27. Rosenzweig, C. *et al.* Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proc. Natl. Acad. Sci.* **111**, 3268–3273 (2014).
28. Stehfest, E., Heistermann, M., Priess, J. A., Ojima, D. S. & Alcamo, J. Simulation of global crop production with the ecosystem model DayCent. *Ecol. Model.* **209**, 203–219 (2007).
29. Auffhammer, M., Ramanathan, V. & Vincent, J. R. Climate change, the monsoon, and rice yield in India. *Clim. Change* **111**, 411–424 (2012).
30. Masutomi, Y., Takahashi, K., Harasawa, H. & Matsuoka, Y. Impact assessment of climate change on rice production in Asia in comprehensive consideration of process/parameter uncertainty in general circulation models. *Agric. Ecosyst. Environ.* **131**, 281–291 (2009).
31. Avnery, S., Mauzerall, D. L., Liu, J. & Horowitz, L. W. Global crop yield reductions due to surface ozone exposure: 1. Year 2000 crop production losses and economic damage. *Atmos. Environ.* **45**, 2284–2296 (2011).
32. Kersebaum, K. C. & Nendel, C. Site-specific impacts of climate change on wheat production across regions of Germany using different CO 2 response functions. *Eur. J. Agron.* **52**, 22–32 (2014).

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Methods (for the online version)

Data. Subnational (state/province level) yield data from 1967 to 2012 were collected from official governmental data bases[33–41]. In a few cases, data was available only from later on (namely in Russia (1996), Ukraine (1992), Indonesia (1969), maize and soybean in India (1977), Brazil (1977) and Argentina (1970)). Using a four-parametric logistic trend (compare Gaupp et al (2016)[16]), annual yield data was de-trended for the analysis. The four-parametric trend was chosen because it is able to capture quasi-linear, concave, exponential or S-shaped trends. Climate data come from Princeton University[42]. The dataset combines global atmospheric reanalysis data with observational datasets to remove biases in the reanalysis. The dataset provides high-resolution climate variables that are consistent in time and space[42,43]. Monthly precipitation, minimum, maximum and mean temperature as well as daily maximum temperature on a 0.5 degree resolution between 1966 and 2012 were aggregated over the breadbasket states and provinces for each crop, as it has been applied, e.g. in

Auffhammer et al[44] . When aggregated to a breadbasket, the climate data was weighted with harvested area following [[20,45]] to account for changes in production regions within the breadbaskets.

Breadbasket selection. The global breadbaskets were selected based on FAOSTAT's[41] country production statistics as well as official governmental statistics on sub national production. For the analysis, the scale of states and provinces was chosen as they provide better accuracy to examine climate and crop yield correlation structures than the national scale[45,46] and, at the same time, there is data available and accessible. The highest crop producing states and provinces of the most important crop producing countries were selected. For Europe, entire countries were chosen as the smallest unit as they are comparable in size with states/provinces in large countries such as China or the US. With the premise that the states/provinces of a breadbasket have to be adjacent, global breadbaskets were defined.

Climate indicator selection. The extensive literature on the relationship between agricultural yield and climatic factors, from both an empirical[20] and model-based[27] perspective, was used to pre-select relevant climate indicators for each region and crop in a multi-step process. Regional case studies were chosen in locations within or very close to the breadbasket areas used in this study. Selected climate indicators are precipitation and temperature based and include both measures based on plant phenology such as number of days above 30°C during the reproductive stage of soybean[47] as well as statistical measures such as the Standardized Precipitation Index[48] (SPI). Although we acknowledge that land-use change and agricultural intensification can influence regional climate via increased evapotranspiration[49,50], in this paper we assume that mostly climate variations impact yields and therefore can be seen as an indicator of breadbasket failure as it has been shown in numerous studies[5,51–53]. In a second step, the pre-selected indicators were reproduced on a state/province scale using Princeton re-analysis climate data[54]. The best fitting indicators for each breadbasket and crop were selected through a correlation analysis with the observed, logistically de-trended sub national crop yield data on state/province level using the Pearson correlation coefficient (results see in Pearson_correl_all_table). Only if the climate-yield relationship suggested in the literature and our own analysis coincided, the climate indicator was chosen for the analysis. In cases in which neither a temperature nor precipitation-based indicator was found significant in our analysis, solar radiation was included as the next important climate variable. In our study, this was the case for rice. Rice is mostly irrigated which can weaken the rice-precipitation relationship, especially when it is not limited through low rainfall[23,55]. As our rice breadbaskets are mainly located in tropical and sub-tropical regions (except for Northern Indian states) where temperature does not vary much, a clear correlation between temperature and rice yields could not be found either. Welch et al. (2010)[55] found that diurnal temperature variation is needed to find a significant temperature-rice yield relationship in the tropics and sub-tropics. Solar radiation was found to be correlated with rice yield in all three breadbaskets. As a result, between one and three indicators per crop and breadbasket were obtained, listed in supplementary table ST1. Climate indicators and harvest periods are summarized in a crop calendar in supplementary figure SF2. In order to analyse changes in climate risks over time, with climate risk defined as the likelihood of a climate indicator exceeding a threshold[1], climate thresholds had to be

[1] We are aware that there are different ways of defining risk. We follow the UNISDR terminology[56] that defines risk as "the combination of the probability of an event and its negative consequences". Using the IPCC's definition[57] of risk as a combination of hazard, exposure and vulnerability, in our study exposure can be interpreted as harvested area (which is kept constant at 2012 levels) and vulnerability as the causal relationship between yield and climate which we include via our extensive literature review, the correlation analysis and

set. Linear regressions between climate indicators and observed crop yield deviations in each state/province were used to define a climate threshold which is related to the lower 25% yield deviation percentile (with 25% as definition of "crop loss" following [[58]]). For a graphical illustration, see supplementary figure SF3. Climate risks as likelihood of the indicator exceeding the threshold were compared for each state/province between two periods, 1967-1990 and 1991-2012 shown in supplementary figure SF4 in order to analyse change over time. For the analysis of simultaneous climate risks, a breadbasket or state/province was defined as "under climate risk" if the threshold of the indicator was exceeded. When a breadbasket has two possible climate indicators, it was defined as "under climate risk" as soon as one of them exceeded the threshold.
To account for uncertainty in the yield-climate relationship, we tested "high-risk" and "low-risk" threshold scenarios by using the upper and lower 90% prediction interval of the linear regression (shown as dashed line in SF3) to calculate "extreme" thresholds. Our results are mostly robust, even when we use those extreme thresholds. For rice, climate risks decrease from period 1 to period 2, independent of the choice of threshold. For wheat, soybean and maize, climate risks increase except for the "high-risk" threshold scenarios for soybean and maize where climate risks decrease in period 2.

Copulas. In order to model likelihoods of simultaneous climate risks, a copula methodology was used. With copulas, non-linear dependencies between continuous random variables can be modelled. Additionally, the method allows modelling the marginal distributions of climate indicators separately from modelling the interdependence between climate indicators within or between breadbaskets. The method goes back to Sklar's theorem[59] which states that the joint distribution function of any continuous random variables (X,Y) can be written as

$$H(x,y) = C[F_X(x), F_Y(y)] \qquad x,y \in \mathbb{R}$$

with marginal probability distributions $F_X(x)$ and $F_Y(y)$ and $C = [0,1]^2 \rightarrow [0,1]$ as copula. If F_X and F_Y are continuous, C is uniquely defined. Different copula types describe different dependence structures. In a multivariate copula model, there are several methods to structure the variables. For this analysis, we used regular vine tree structures, RVines[60–62], which use different conditional and unconditional bivariate pair-copulas to decompose the multivariate probability density of the different climate indicators. RVines are most flexible in modelling complex dependencies in larger dimensions. A d-dimensional vine structure consists of (d-1) trees with N_i nodes and E_{i-1} edges joining the nodes. A tree structure is built following the proximity condition which states that if an edge connects two nodes in tree j+I, the corresponding edges in tree j share a node[62]. In this paper, we select trees using a maximum spanning tree algorithm with Kendall's tau as edge weight[63]. For each copula-pair, the best-fitting copula family is selected from a list of six families, namely Gaussian, Student-t, Clayton, Gumbel, Frank and Joe as well as their rotated versions to capture negative dependencies. These include tail symmetric or asymmetric as well as tail dependent and not tail dependent copula families. The best fitting copula family is then chosen using the Akaike information criterion[64]. The parameters for each bi-variate copula are derived with a maximum likelihood estimation. Together with fitted and simulated marginal distributions for each state/province, joint distributions are derived. In the global scale analysis, intra-breadbasket dependencies are kept when the dependence structure between the

threshold calculation using the linear regression. Hazards can be interpreted as likelihood of climate indicators threshold exceedance. Hence, a change in climate risk are due to a change in hazards, following the IPCC definition.

breadbaskets is modelled following the hierarchical structuring method[16]. To account for sampling uncertainty, we repeated the simulation of univariate marginal, joint dependency 1000 times and used the average. The standard error of the 1000 simulations is shown with the error bars in figures 1, 2, SF4, SF5 and SF6. The analysis was conducted using CRAN R with the packages 'copula', 'CDVine' and 'VineCopula'.

Data availability

Crop yield data are taken from official governmental databases: Data from Argentina can be accessed at http://www.siia.gov.ar/; from Australia at https://www.abs.gov.au; from Brazil at http://www.conab.gov.br; from China at http://data.stats.gov.cn/; from Europe and the Ukraine at http://www.fao.org/faostat/en; from India at http://eands.dacnet.nic.in/; from Indonesia at https://www.bps.go.id/linkTableDinamis/view/id/865; from Russia at http://cbsd.gks.ru/ and from the US at http://quickstats.nass.usda.gov.

Climate re-analysis used in our analysis can be accessed at http://hydrology.princeton.edu/data/pgf/.

Code availability

The R script written to read and analyze data and generate figures can be accessed at: https://github.com/FranziskaGaupp/Simultaneous_BB_failure.

33. Ministerio de Agricultura, Ganaderia y Pesca de Argentina. Statistical database. (2015).
34. Ministry of Agriculture and Farmers Welfare, Govt. of India. Crop Production Statistics. (2015).
35. USDA. Economics, Statistics ad Market Information System. (2015).
36. National Bureau of Statistics of China. Regional data.
37. Conab (Companhia Nacional De Abastecimento) Brazil. Séries históricas. (2015).
38. Australian Bureau of Statistics. Historical Selected Agriculture Commodities. (2015).
39. Federal State Statistics Service, Russia. Statistical database. (2018).
40. Statistics Indonesia. Statistical database. (2018).
41. FAOSTAT. (2015).
42. Sheffield, J., Goteti, G. & Wood, E. F. Development of a 50-year high-resolution global dataset of meteorological forcings for land surface modeling. *J. Clim.* **19**, 3088–3111 (2006).
43. Sheffield, J., Wood, E. F. & Roderick, M. L. Little change in global drought over the past 60 years. *Nature* **491**, 435 (2012).
44. Auffhammer, M., Ramanathan, V. & Vincent, J. R. Integrated model shows that atmospheric brown clouds and greenhouse gases have reduced rice harvests in India. *Proc. Natl. Acad. Sci.* **103**, 19668–19672 (2006).
45. Ray, D. K., Gerber, J. S., MacDonald, G. K. & West, P. C. Climate variation explains a third of global crop yield variability. *Nat. Commun.* **6**, (2015).
46. Osborne, T. M. & Wheeler, T. R. Evidence for a climate signal in trends of global crop yield variability over the past 50 years. *Environ. Res. Lett.* **8**, 024001 (2013).
47. Schlenker, W. & Roberts, M. J. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proc. Natl. Acad. Sci.* **106**, 15594–15598 (2009).

48. McKee, T. B., Doesken, N. J., Kleist, J. & others. The relationship of drought frequency and duration to time scales. in *Proceedings of the 8th Conference on Applied Climatology* **17**, 179–183 (American Meteorological Society Boston, MA, 1993).
49. Mueller, N. D. *et al.* Cooling of US Midwest summer temperature extremes from cropland intensification. *Nat. Clim. Change* **6**, 317–322 (2016).
50. Mueller, N. D. *et al.* Global Relationships between Cropland Intensification and Summer Temperature Extremes over the Last 50 Years. *J. Clim.* **30**, 7505–7528 (2017).
51. Lobell, D. B. & Asseng, S. Comparing estimates of climate change impacts from process-based and statistical crop models. *Environ. Res. Lett.* **12**, 015001 (2017).
52. Luo, Q. Temperature thresholds and crop production: a review. *Clim. Change* **109**, 583–598 (2011).
53. Doorenbos, J. & Kassam, A. H. Yield response to water. *Irrig. Drain. Pap.* **33**, 257 (1979).
54. Shepherd, T. G. Atmospheric circulation as a source of uncertainty in climate change projections. *Nat. Geosci.* **7**, 703–708 (2014).
55. Welch, J. R. *et al.* Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proc. Natl. Acad. Sci.* **107**, 14562–14567 (2010).
56. Burton, I. *et al.* UNISDR Terminology on Disaster Risk Reduction (2009). *Int. Strategy Disaster Reduct.* (2015).
57. Field, C. B. *et al. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of IPCC Intergovernmental Panel on Climate Change*. (Cambridge University Press, 2012).
58. Richter, G. M. & Semenov, M. A. Modelling impacts of climate change on wheat yields in England and Wales: assessing drought risks. *Agric. Syst.* **84**, 77–97 (2005).
59. Sklar, M. *Fonctions de répartition à n dimensions et leurs marges*. (Université Paris 8, 1959).
60. Aas, K., Czado, C., Frigessi, A. & Bakken, H. Pair-copula constructions of multiple dependence. *Insur. Math. Econ.* **44**, 182–198 (2009).
61. Kurowicka, D. & Cooke, R. M. *Uncertainty analysis with high dimensional dependence modelling*. (John Wiley & Sons, 2006).
62. Bedford, T. & Cooke, R. M. Vines: A new graphical model for dependent random variables. *Ann. Stat.* 1031–1068 (2002).
63. Dißmann, J., Brechmann, E. C., Czado, C. & Kurowicka, D. Selecting and estimating regular vine copulae and application to financial returns. *Comput. Stat. Data Anal.* **59**, 52–69 (2013).
64. Akaike, H. Information theory and an extension of the maximum likelihood principle. Á In: Petran, BN and Csáki, F. in *International symposium on information theory, Second edition. Akadémiai Kiadi, Budapest, Hungary, pp. 267Á281* (1973).