Letter

Changing risks of simultaneous global breadbasket failure

The risk of extreme climatic conditions leading to unusually low global agricultural production is exacerbated if more than one global 'breadbasket' is subject to climatic extremes at the same time. Such shocks can pose a risk to the global food system amplifying threats to global food security[1,2] and have the potential to trigger other systemic risks[3,4]. So far, while the possibility of climatic extremes hitting more than one breadbasket has been postulated[5,6] little is known about the actual risk. Here we present quantitative risk estimates of simultaneous breadbasket failures due to climatic extremes and show how risk has changed over time. 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') in the world. We find evidence that there is 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 breadbaskets analyzed in this study 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[7]. Under 'normal' climatic circumstances the global food system can compensate local crop losses through grain storage and trade[8]. However, it is doubtful whether the global food system is resilient to more extreme climatic conditions[9], when export restrictions[10] 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[1] and famine[2], with the potential to trigger other systemic risks including political unrest[3] and migration[4]. 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, therefore posing a risk to the global food system[8,10], 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[5,6], only few studies have investigated the probability of simultaneous production shocks [13] or estimated the joint likelihoods of adverse climate conditions [14]. Here we present, to our knowledge for the first time, 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.

Changing climatic risks in food producing regions

We analyzed climatic and crop yield data (see Supplementary Material 1 and 2.1) 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 and Supplementary Material 2.3). 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[15,16] that reports a significant increase in temperature extremes in China in recent decades.

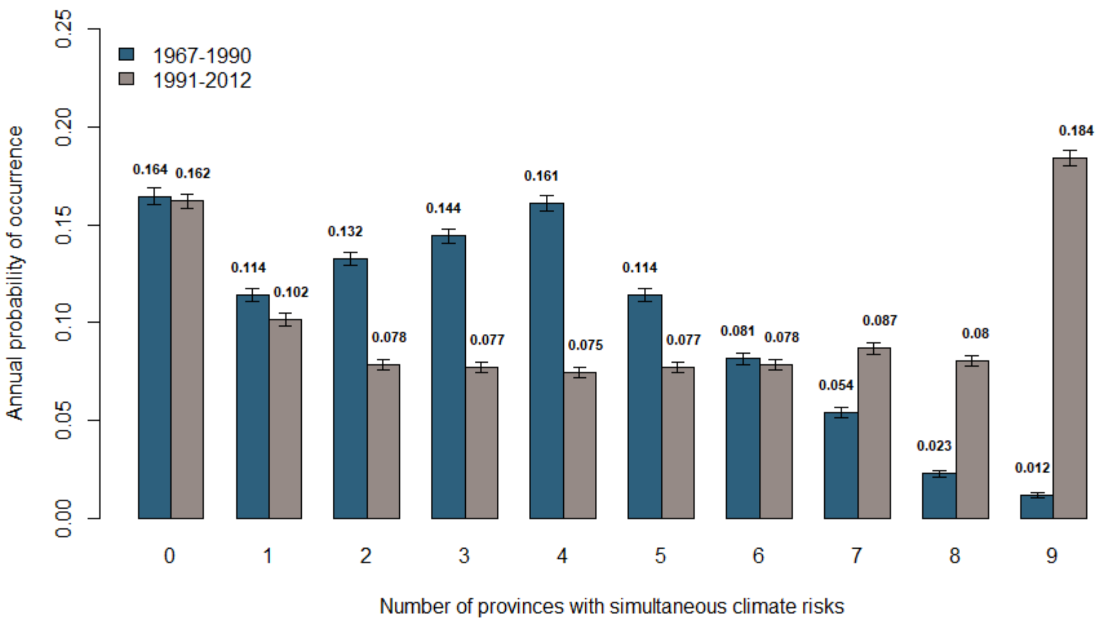

Figure 1: Likelihood of simultaneous climate risks in the 9 most important soybean producing provinces in China threatening agricultural production: defined as relevant climate indicators exceeding the value that corresponds to the to the lower 25% yield deviation percentile. The error bars indicate the standard error based on bootstrapping (Supplementary 2.3).

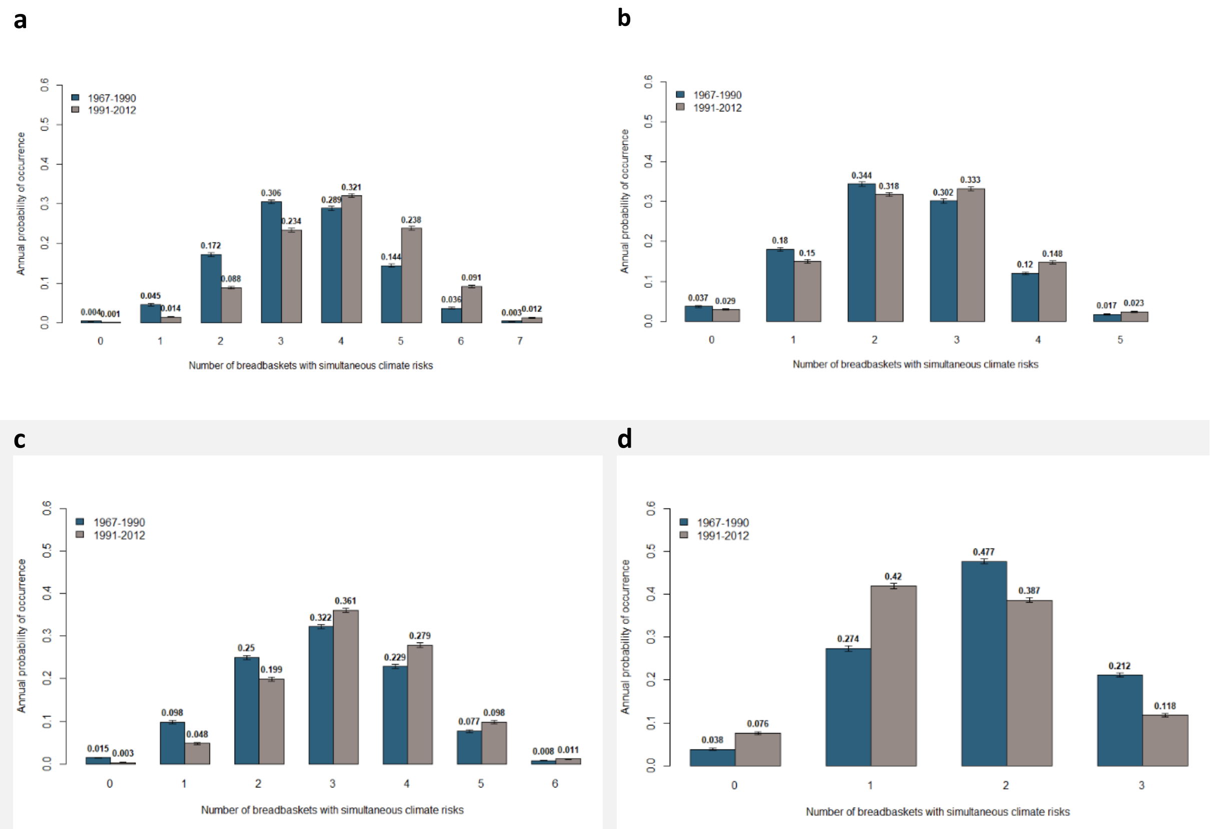

Figure 2: Likelihood of climatic conditions simultaneously threatening crop losses in the global breadbaskets: defined as relevant climate indicators exceeding the value that corresponds to the to the lower 25% yield deviation percentile. (A) wheat (b) soybean (c) maize and (d) rice breadbaskets.

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[7,17], precipitation often has no substantial impact on rice production as rice is mostly irrigated[18–20]. Moreover, there is no discernable temperature effect in Indonesia because temperatures are generally below the critical thresholds during rice growing season[21]. In China, temperature effects depend largely on the region[22] 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 Supplementary Material 3.5. 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[6]. 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[6] .

Spatial dependence between global breadbaskets

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 Material 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[23], 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).

Discussion

Analysis of climatic risks to crop production has conventionally used crop models on a global scale[24]. Whilst crop-models can incorporate complex time-dependent climatic influences on yield, there is a mismatch between model predictions and actual yield data[24,25]. 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[21,26,27]. 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[28,29]. Owing to limited data availability, we could not consider agronomic factors such as irrigation, pest infestation or different crop varieties. This study represents, to our best knowledge, 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.

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Methods (for the online version)

The extensive literature on the relationship between agricultural yield and climatic factors, from both an empirical[17] and model-based[24] perspective, was used to identify relevant climate indicators in a multi-step process (see Supplementary Material 3.2). We focused upon the climatic indicators that significantly influenced yields. A list of selected climate indicators for each crop and breadbasket are available in Supplementary Table ST1. Indicators include both statistical measures such as the Standardized Precipitation Index[30] (SPI) as well as measures based on plant phenology such as number of days above 30°C during the reproductive stage of soybean[31]. Depending on the fit between literature values and the results of our data analysis, between one and three indicators per crop and breadbasket were selected. We analyzed the probability of selected climatic indicators exceeding the value associated with yield deviations being in the lower 25 percentile (see Supplementary Material).

To analyze the dependence structure between these relevant climatic variables at regional and global scales we used the copula methodology. We applied regular vine copulas (RVines) which model high dimensional statistical dependencies. RVines are able to decompose a multivariate probability density using a cascade of unconditional and conditional bivariate pair-copulas. These pair-copulas are ordered in tree-structures, which are built using maximum spanning trees with Kendall's tau as edge weights. Pair-copulas are chosen from a list of copula families with different characteristics using the Akaike information criterion and parameters are estimated with a maximum likelihood estimation (see Supplementary Materials).

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