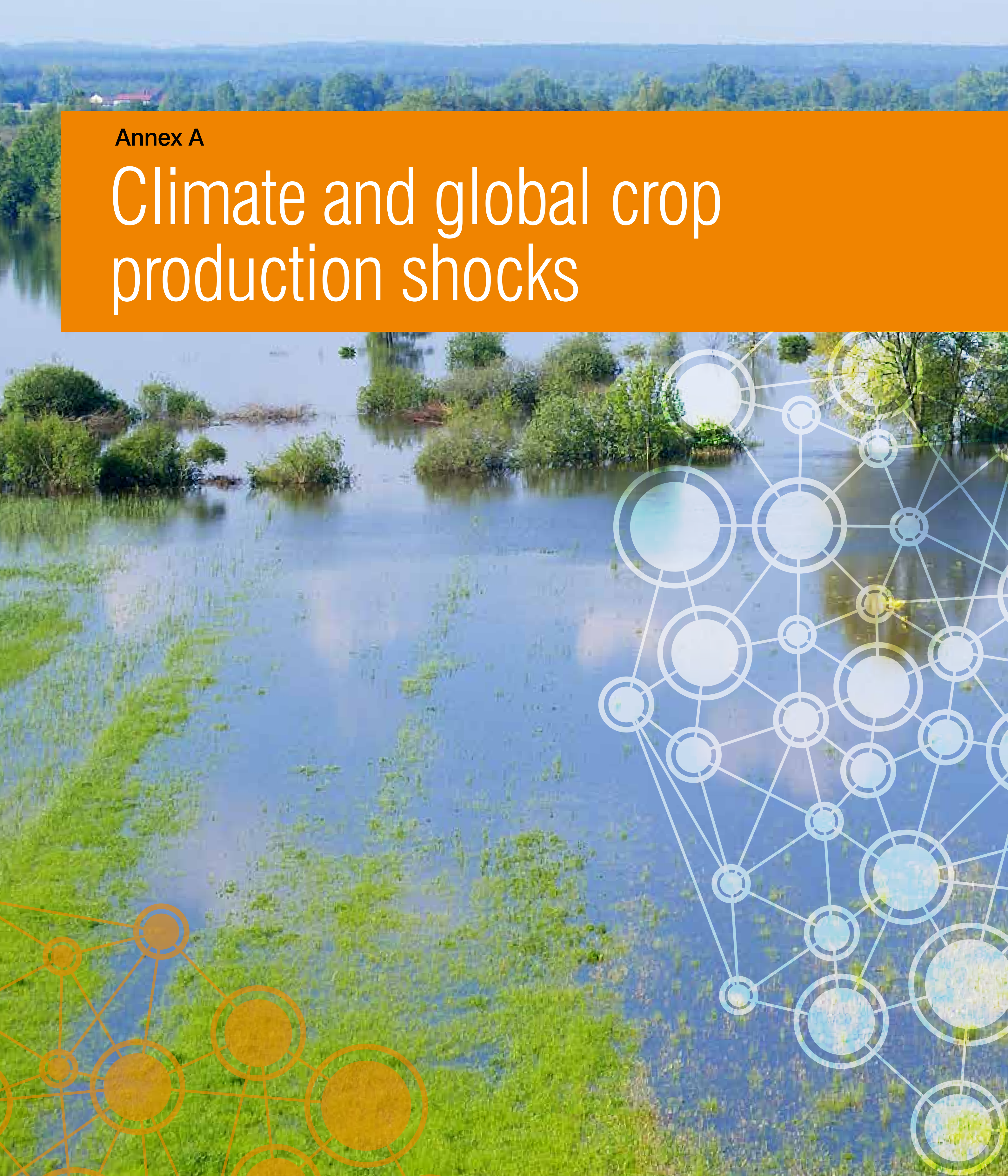
RESILIENCE TASKFORCE SUB REPORT

Annex A

Climate and global crop production shocks



Foreign & Commonwealth Office

UK Science & Innovation Network

Global Food Security
Sustainable, healthy food for all

Contents

This report originates from a Taskforce of academics, industry and policy experts to examine the resilience of the global food system to extreme weather events. The Taskforce was brought together by the UK's Global Food Security programme and was jointly commissioned by the UK Foreign and Commonwealth Office and UK Government Science and Innovation Network. This report on Climate and global production shocks sits in the context of two other detailed reports on Country level impacts of global grain production and a Review of the responses to food production shocks. There is also an overall Extreme weather and resilience of the global food system summary report.
The contents of these reports are based upon workshop discussions held at Willis Tower, Chicago in October 2014 and the Foreign and Commonwealth Office, London in February 2015 (see the Synthesis report for a full participant list).

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Electronic versions of the report series may be found at the addresses below:

Extreme weather and resilience of the global food system summary report
www.foodsecurity.ac.uk/assets/pdfs/extreme-weather-resilience-of-global-food-system.pdf

Climate and Global Crop Production Shocks
www.foodsecurity.ac.uk/assets/pdfs/climate-and-global-crop-production-shocks.pdf

Review of the responses to food production shocks
www.foodsecurity.ac.uk/assets/pdfs/review-of-responses-to-food-production-shocks.pdf

Country level impacts of Global Production Shocks
www.foodsecurity.ac.uk/assets/pdfs/country-impacts-of-global-grain-production-shocks.pdf

Front cover: Frank Havemann

Executive summary and key messages

- The current global food production system is at risk of shocks from extreme weather.
- Food production for four major crops (maize, soybean, wheat and rice) is located in a small number of major producing countries, with a large amount of overlap across the crops. This means that the exposure of a large proportion of global production of the major crops is concentrated in particular parts of the globe, and so extreme weather events in these regions have the largest impact on global food production.
- The US, China and India emerge as major breadbasket producers. There is a risk of simultaneous multiple breadbasket failures. This risk has not yet been quantified. There is an urgent need to understand driving dynamics of meteorological teleconnections in order to quantify the likelihoods of coincident production shocks in major food-producing regions.
- By examining production shocks in the recent past, we see that weather events, particularly drought, are a major driver of these shocks.
- Using the example of past events we generated a set of scenarios of weather-driven production shocks, for each of the four crops, that are plausible in the present or near future climate.
- These scenarios include production shocks of the order of a 10% decrease in global production for each of the four major crops.
- Climate science research offers the opportunity to explore what climate change may mean for the future risks of food production system shocks from extreme weather, primarily through the use of climate models and crop models.
- What we would call a rare extreme food production shock in the late 20th century is likely to become more common in the future. We present evidence from a recent international study using crop models suggesting that a 1-in-100-year production loss from the 20th century may be as frequent as 1-in-30 in just a few decades.
- It is difficult to evaluate the likelihood of rare, extreme events, without having access to large amounts data. There is therefore a need for long runs of high resolution global climate model data simulating the current and future climate, to estimate the risks posed by extreme events.
- Crop model research is needed to improve representation of physiological mechanisms, genetic variation and improvement in response to extreme growing conditions.
- Understanding the interactions between average production increases, variability, and resilience to extreme events is crucial to future food security.
- Also required, is further investigation into the meteorological teleconnections between major food production regions, and the probability of coincident shocks in multiple breadbaskets, both now and in the future

Frank Havemann

Introduction

1.1 Increases in temperature of over two degrees Celsius are expected to have a negative impact on global yields of major crops (IPCC 2014). Projected impacts are spread unevenly over the globe with crop production in low latitudes expected to experience negative effects whereas in northern latitudes impacts may vary. The areas where climate change is expected to most threaten crop productivity (Wheeler & von Braun, 2013) include countries in Africa and South Asia that are home to many of the world's 805 million undernourished people (FAO, 2014).

1.2 Reduction in yield and increased variability from extreme weather events is likely to increase the long-term mean and volatility of staple food prices (Tadesse et al 2014). It is therefore vital to further understand the impacts of climate change on future crop yields, both in terms of long-term means and variability. The Foresight report suggests that food production must be increased by 70% by the year 2050 and that failure to achieve this could contribute to deterioration in peace and security (UK Government, 2011).

1.3 The focus of this study was on high impact weather events in the largest producing areas for each of the four major global crops (maize, soybean, wheat and rice). Extreme events in large producing areas will have big impacts on the global market, however extremes in small production areas could still have significant impacts on local food security. The aim of the study was to generate a set of scenarios of weather-driven global food production shocks that are plausible in the present day or near-future climate. These scenarios form the basis of additional work looking at the impacts of these production shocks on food prices and food security.

1.4 The study looked at both observational evidence of past production shocks and their relationship to weather, as well as using crop models to simulate the impact of weather on past production. This approach was taken in order to ground the study in the reality of the experience of the impact of weather events on the global production system as a whole, to ensure that the resultant scenarios were both plausible and salient.

1.5 In addition the use of climate model and crop model data is discussed as a means to explore future change in risk of weather-driven production shocks. Some initial results from this discussion are presented.

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Methods

2.1 The use of both historical events (data) and projections (models) is particularly important when assessing the likelihood and impact of extreme events. Historical events include all real-world yield-impacting phenomenon that models either leave out or represent poorly, such as flood, pests, disease, and conflict (just to name a few). Historical events also have the benefit of being demonstrably plausible and of the fact that historical responses and consequences can, in principle, be known. While historical extreme events thus provide useful analogues for present-day and near-future events (see e.g. Battisti & Naylor, 2009), they pose some significant challenges for constructing useful and plausible extreme scenarios. First, they do not explicitly take into account future climate conditions which may significantly impact the size, scale, and frequency of extreme events in the near future. Additionally, because of rapidly changing technology, patterns of agricultural land-use and land-cover, and even political climates and wars, it is often difficult to compare an event separated in time by one or more decades. Finally, the relatively small sample-size available makes it impossible to resolve the tails of the anomaly distribution (i.e. identify the likely scale of a rare event with return times of 100 years or more).

2.2 Evaluating extreme events with crop-climate models provides a complementary perspective. Crop-climate models are the only way of generating data on extreme events that explicitly takes into account future conditions. Additionally, crop-climate models, driven by ensembles of simulated climate conditions, allow us to generate the large samples that are required to robustly evaluate the statistics of extreme events in the far tails of the distribution. Finally, crop-climate models also help us to understand the drivers of historical extreme events and identify the extent to which the yield or production anomaly in a given year was caused by climatological factors. Even so, the accuracy of models is limited by any number of uncertainties and, though important international projects are ongoing, the global community has yet to develop the full range of multi-model ensemble data products and intercomparisons required to address this question in a satisfactory way.

2.3 In this project, we have employed both of these methods to develop plausible future crop-climate extreme event scenarios for each of the four biggest global crops (maize, soybean, wheat, and rice) and for global calorie production as a whole. In each case we have used a combination of historical data and crop-climate models to select significant negative events from the last 50 years and use the relative country-level yield and production anomaly from these years as a template for generating a plausible present-day or near-future extreme event.*

Geography of crop production

3.1 Each crop has a different geographic distribution, which affects its exposure to weather and climate events. Table 1 shows the top 10 producing countries of the four main crops, and the percentage of global production for each country. Among the major crops, wheat is relatively widely distributed, while maize and soybean are especially concentrated in a small number of countries. Almost two thirds of the soybeans produced globally come from either the US or Brazil (and including nearby Argentina the production fraction is more than 80%).

3.2 Similarly, almost 60% of maize production comes from the US or China, however the other 40% is more distributed. About half of the world's rice production comes from China or India and nearly another third is produced in Southeast Asia. This high level of concentration, which has generally increased over the last several decades, makes the global food supply even more sensitive to large-scale climate extremes.

	Maize	**Soybean**	**Wheat**	**Rice**
1	US (39.17)	US (38.07)	China (16.41)	China (28.83)
2	China (19.62)	Brazil (24.89)	India (11.81)	India (21.24)
3	Brazil (6.33)	Argentina (17.8)	US (9.17)	Indonesia (8.86)
4	Mexico (2.93)	China (7.26)	Russia (7.82)	Bangladesh (6.54)
5	Argentina (2.39)	India (4.03)	France (5.81)	Vietnam (5.69)
6	India (2.2)	Paraguay (2.16)	Canada (3.77)	Thailand (4.77)
7	France (2.01)	Canada (1.4)	Germany (3.71)	Myanmar (4.39)
8	Indonesia (1.79)	Bolivia (0.72)	Pakistan (3.38)	Philippines (2.34)
9	South Africa (1.38)	Indonesia (0.36)	Australia (3.17)	Brazil (1.82)
10	Canada (1.34)	Russia (0.32)	Turkey (3.14)	Japan (1.7)
Total	**79.2%**	**97%**	**68.2%**	**86.2%**

Table 1: Top producing regions based on FAOSTAT 2001-2010 average production values (FAOSTAT, 2015). Brackets indicate percentage of global production.

* *The work utilises the 5-year rolling mean method for detrending the yield/production/area anomalies.*

Evaluating past events from observational data

4.1 We identified extreme negative anomalies for production, yield, and area within the approximately 50 year period of the country-level FAO dataset. Each was evaluated to choose good candidate years to use as agro-climatological 'templates' for plausible present-day and near-future extreme event scenarios. This methodology is described here in detail, along with the resulting scenario, for maize; template years and plausible extreme event scenarios for other crops are selected in a similar manner (see Appendix A).

The geography of maize production

4.2 The two largest maize producing countries are the US and China, which between them produce almost 60% of the total maize grown in the world. The next largest producer, Brazil accounts for just over 6% of production, and the next seven largest have 1-3% of the total each. This means that total global maize availability is disproportionately affected by production and trade activity in just two countries, although production in Brazil has the potential to have some impact too. Figure 1 shows a map of the world with the major maize producing countries shaded in green. The relatively high importance of production in the US and China, in global terms, means that studies of the impacts of climate change on maize and food security can concentrate on these two major producing regions. Climate events that impact production in either country will have global consequences, and the relationship between weather events in each (i.e. the coincidence of high impact weather in the two locations), is of critical importance. This suggests that for maize in particular, there should be a focus on the relationship between weather and production in the US and China, in order to understand global food security impacts.

Selecting a template year from historical production shock case studies

4.3 Like all of the four main crops included in this study, maize has seen a large increase in production over time (Figure 2). The total production has increased approximately five fold from 1960 to 2012, from 200 million tonnes per year, to 1 billion tonnes per year. This is a result of a both a steady increase in yield over that time, and an increasingly rapid expansion of harvest area.

4.4 At the global scale, large maize production anomalies occurred during 1983, 1988 and 2006. Yield and area harvested anomalies drove the negative production in 1983, whilst yield and area harvested anomalies independently drove the production anomalies in 1988 and 2006 respectively. There are two clear significant negative yield anomalies for maize, occurring in 1983 and 1988. A corresponding production decrease occurred in both years; however for 1983 this was also driven by a large decrease in the area harvested. Spatially, the global yield anomalies in both 1983 and 1988 were driven by large yield decreases in the US, the top maize producer.

4.5 In 1983 (Figure 3, top panel) the US accounted for the majority of the reduction in production with other large losses in Brazil, Argentina and South Africa. Some of the production loss was however balanced by increases in other top producers, driven by positive anomalies in yield (India), area harvested (China), or both (Indonesia). In 1988 (Figure 3, bottom panel) the yield decrease in the US was almost twice as large as that seen for any of the top 10 maize producers. Yield and area harvested increases in France and Argentina provided a maize production increase however this was approximately two orders of magnitude smaller than the loss experienced in the US. Normalised to the year 2002 values, the 1988 US damages are estimated to be approximately $61 billion to agriculture and related industries (Lott and Ross, 2006).

4.6 Recent literature indicates a strong relationship between droughts and maize production in the US; particularly soil moisture, rainfall and maximum temperatures during June and July, when the majority of maize is grown (Chung *et al*., 2014; Lobell *et al*., 2013; Westcott and Jewison, 2013; Handler, 1990).

4.7 In June 1988 the average temperature across the US Corn Belt was approximately 2°C above the long term average, whilst rainfall was below average by over 60mm (~60%) (NOAA, 2015). Furthermore, July 1988 experienced slightly above average temperatures and a negative rainfall anomaly of almost 20mm (~-15%). Across the entire growing period (May-October) 1988 ranks as the driest Palmer Drought Severity Index (PDSI) – a measure of soil moisture conditions – and lowest rainfall total in the period 1980-2014 (Figure 4).

4.8 The US growing period PDSI and precipitation totals (Figure 4) however do not highlight 1983 as an anomalous year; for much of the growing period conditions were approximately average across the Corn Belt. Instead it appears to be above average temperatures and below average rainfall in July, and particularly for August, which impacted maize production. There is little information on the synoptic scale drivers of these conditions, however, it is noted that a strong El Niño event from 1982/1983 decreased in strength and became La Niña during 1983. This could be important as ENSO events are associated with rainfall

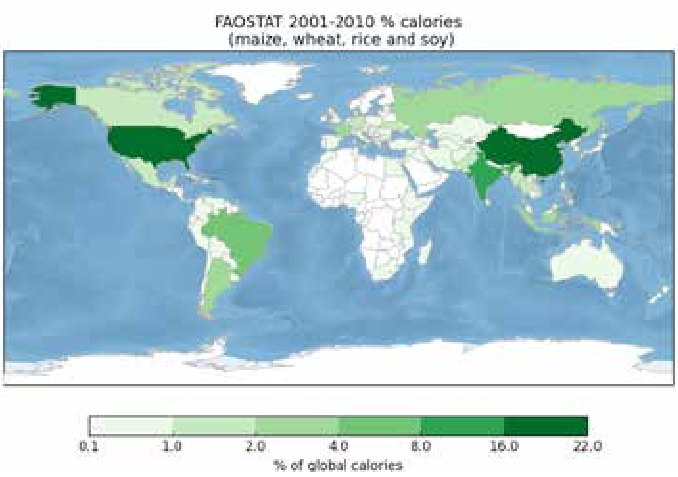

Figure 1: Proportion of total global maize production grown by country (2001-2010 average). *Source FAOSTAT (2015)*

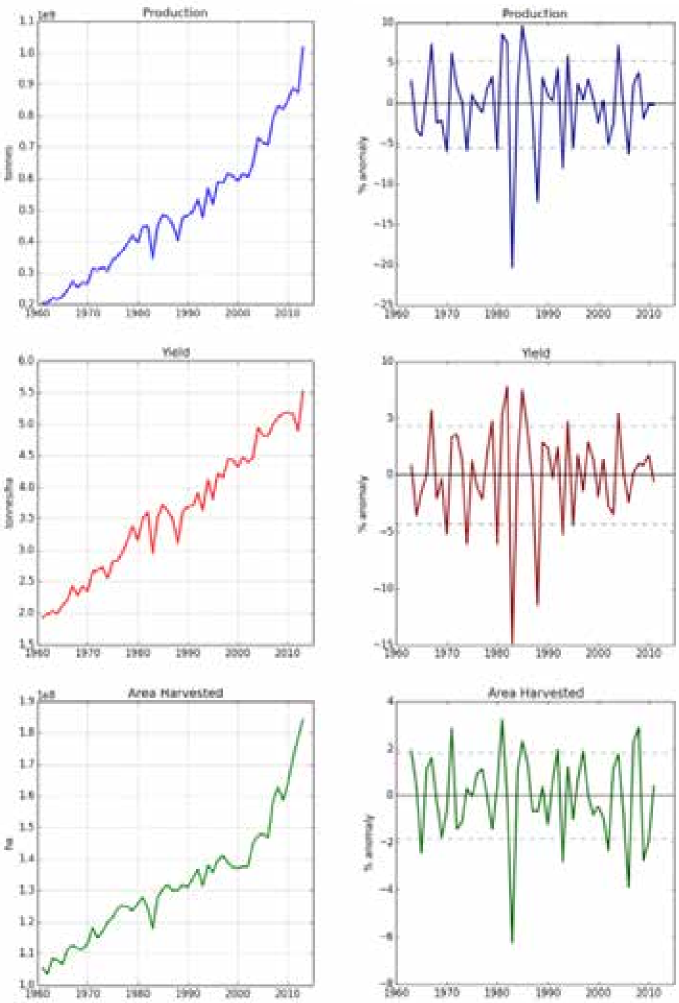

Figure 2: Global production, yield and harvested area data for maize from 1960 to 2012. *Source: FAOSTAT (2015)*

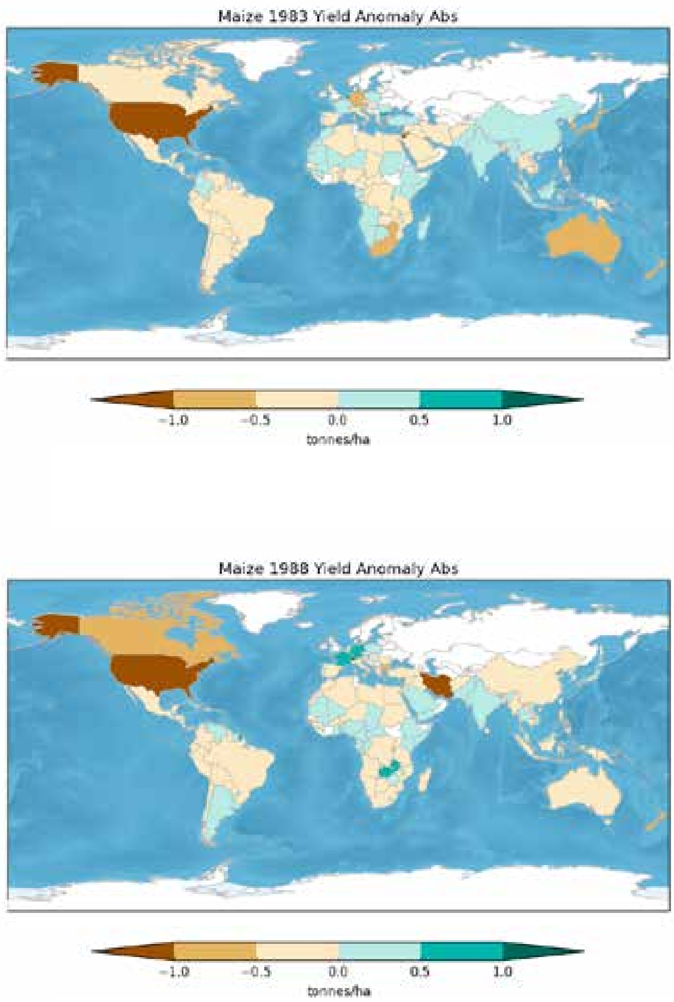

Figure 3: Detrended FAOSTAT country level maize yield anomalies (tonnes per hectare) for 1983 (top) and 1988 (bottom). *Source FAOSTAT (2015)*

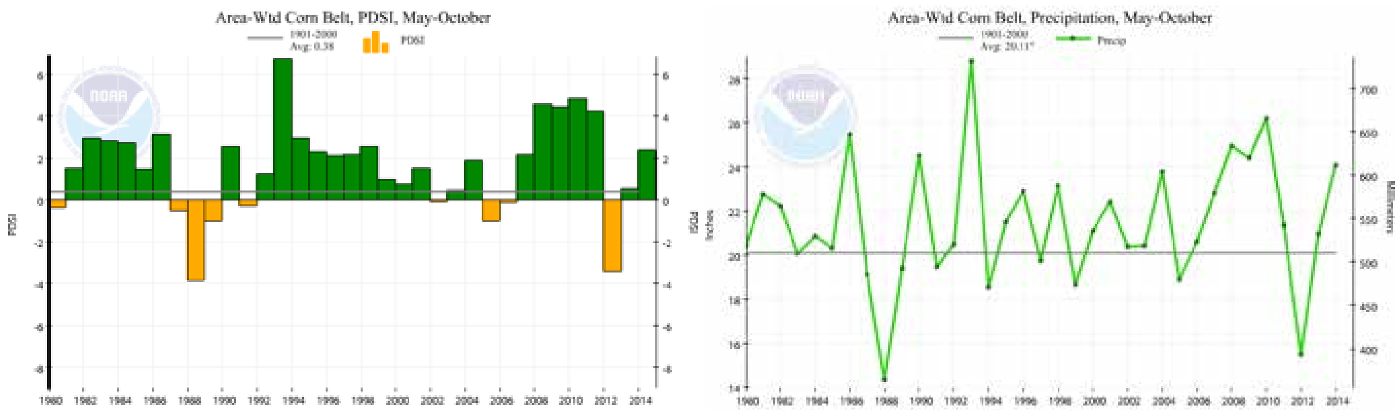

Figure 4: US Corn Belt May-October PDSI (left) and precipitation (right). *Source: National Centres for Environmental Information (NOAA) (2015).*

and temperature anomalies across the continental US (Peterson *et al*., 2013).

4.9 During 1983, negative yield anomalies were also experienced over South America and South Africa. As with the US, both regions experienced low rainfall and drought conditions which may have been linked to the 1982/1983 El Niño event (Rouault and Richard, 2003, Sun *et al*., 2007).

Understanding the probability of extreme climate events

5.1 Looking at past events from FAO observational data of global crop production and investigating the driving meteorology, is a useful way to understand more about the relationship between climate extremes and global food production. However, there are limitations to this approach. The three main limitations are as follows: Firstly, that we only have data on events that actually occurred, and then over a relatively short period of time. This means it is difficult to evaluate the probability of an event, given such a small sample data set. Secondly, agricultural systems have developed substantially over time, making it difficult to compare production shocks separated by many years. The area under cultivation has increased hugely for all four crops, and technology, the use of fertilizers and pesticides, as well as farming methods have all resulted in large increases in yield. The result is that examples of production shocks in the past may not be particularly representative of the risks associated with shocks in the present or near future. Finally, the production shocks themselves could be driven by a wide range of events, not necessarily meteorological, also making it difficult to evaluate the risks associated with climate events alone.

5.2 Despite these limitations, the observational events are a useful means of creating complex, realistic and plausible representations of production shocks, and so form the basis of the scenarios developed in this study. In order to address some of the limitations, we combine this historical approach with model-based assessments driven by historical data and climate model output. This allows us to separate climate-driven events in the historical record from non-climate events and greatly extend the size of the considered sample so that we can begin to assign probabilities and return times to individual events.

5.3 Figure 5 shows an example for global maize productivity, comparing detrended global FAO anomalies with the results from a single global crop model (the pDSSAT model (Elliott *et al* 2014a) driven by climate forcing data from the Princeton Global Forcing Dataset (Sheffield *et al* 2006)) from the Global Gridded Crop Model intercomparison (GGCMI) project (Elliott *et al* 2015). Here the model and FAO data agree quite well over the overlapping period and both convincingly find 1988 to be the most severe recent year. Assuming the historical yields are distributed normally around the mean, 1988 is estimated to be 2.5 to 3 standard deviations from the mean. However, given the asymmetry (negatively skewed) of the yield anomaly distribution, this event is likely to occur much more often than this suggests. Either way, we can be confident that 1988 was the most severe event in the last 6 decades and was largely driven by climatological factors, making it a good template year for constructing a plausible extreme production shock event.

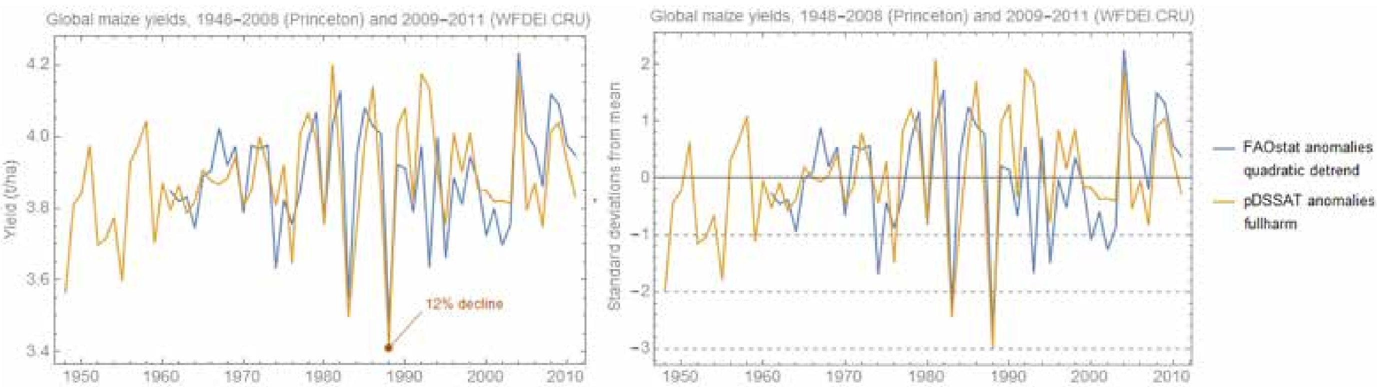

Figure 5: Comparison showing FAO data and model output for global maize productivity, using only a single processing methodology in both cases.

Developing a global production shock scenario

6.1 From the data available on the geography of global maize production, the examples investigated from the case study year events, and the model-based analysis of historical extremes, the following scenario for maize was developed (Table 2). This outlines representative changes in production levels, based on the actual events of 1988. Similar scenarios are developed for the other major crops (see Appendix A). Table 3 summarizes the template years chosen for each of the four crops, and gives the global production loss estimated from the historical and simulated anomalies.

Country	Harvest period	% production decrease*	Absolute production loss (tonnes)	Driving meteorology
US	Sept-Nov	31%	56,432,003	Drought
China	July-Oct	4%	3,281,670	
Canada	Sept-Nov	16%	1,017,300	Drought
Mexico	Apr-July	11%	1,347,155	
Global		12%	55,867,720	Driven by US

** % of national total*

Table 2: Scenario figures for a maize production shock (based on 1988 case study)

Country	Case study year	% Production decrease	Absolute production loss (million tonne)	Modelled yield loss from GGCMI (%)
Maize	1988	12%	55.9	13.5-16.4
Soybean	1988/89	8.5%	8.9	6.0-6.3
Wheat	2003	6%	36.6	6.4-9.5
Rice	2002/03	4%	21.7	1.9-3.5

Table 3: Global scenario figures for production shocks.

State of climate science

7.1 The scenarios developed in this study are the result of an assessment of recent past weather-driven global production shock events. However, the climate is changing, and in order to understand what this means for the risks associated with future production shocks, climate scientists rely on a combination of an understanding of the physical, dynamical processes that drive the Earth's system, and climate models to simulate that system. Whilst no model is perfect, climate models have proven remarkably accurate in forecasting the climate change we've experienced to date. In a few cases, model projections have been overly conservative, for example, in projecting how quickly Arctic sea ice would decline. It has in fact declined more rapidly than the models forecast. Today's climate models encapsulate the great expanse of current understanding of the physical processes involved in the climate system, their interactions, and the performance of the climate system as a whole. They are extensively tested relative to observations and are able to reproduce the key features found in the climate of the past century.

7.2 Because models differ in their representation of certain processes, we make use of these differences by examining suites of models in climate assessments. However, they all give the same basic story. Also, despite the tremendous improvements in the climate modelling capabilities over the last 45 years since the first model was developed, the basic response of a significant effect on the climate system from human activities continues to be about the same as the models were finding then. These models are the only crystal balls we have – and although not perfect, they are very useful tools.

7.3 The computational power required by climate models can be thought of as falling into three categories. First, the model must solve physical equations, which become more computationally expensive the more complex – and therefore realistic – the model becomes. Second, since the equations are solved on a grid that covers the globe, high resolution is needed in order to capture weather systems and other processes adequately. High resolution is particularly important when projecting extreme events. Third, since climate prediction is inherently uncertain, multiple model runs, often involving a range of models, need to be run. These model ensembles aim to capture the range of possible futures and provide an indication of the likelihood of the outcomes within that range. They also allow for better understanding of the role of natural variability in future climate changes. In general, the greater the size of the ensemble, the greater the confidence in the spread obtained. In projecting extreme events multiple simulations, and/or simulation of very long periods of time, becomes particularly important. By their nature extreme events are rare, so that many years of simulations are needed in order to capture information regarding their frequency.

7.4 Although the overall change in average climate itself is certainly important, much more important to society and to agriculture are the changes occurring in severe weather. There is strong evidence of an increasing trend over recent decades in some types of extreme weather events, including their frequency, intensity, and duration (Min *et al.*, 2011; IPCC, 2012, 2013; Trenberth & Fasullo, 2012; Zwiers *et al.*, 2013; Wuebbles *et al.*, 2014; Janssen *et al.*, 2014). Analyses by NOAA in the U.S. and by Munich Re and other organizations (Rauch, 2011; Meyer *et al.*, 2013) show that there is an increasing cost on our society from an increasing trend in severe events. Observations show increasing trends worldwide in the number of extremely hot days, fewer extreme cold days, more precipitation events coming as unusually large precipitation, and more floods in some regions and more drought in others (IPCC, 2012, 2013). High impact, large-scale extreme events are complex phenomena involving various factors that come together to create a "perfect storm." Such extreme weather obviously does occur naturally. However, the influence of human activities on global climate is altering the frequency and/or severity of many of these events (IPCC, 2012, 2013). Observed trends in extreme weather events, such as more hot days, fewer cold days, and more precipitation coming as extreme events, are expected to continue and to intensify over this century (IPCC, 2012, 2013). Figure 6 shows the increasing trend in the Extreme Precipitation Index based on observations over the continental United States. Similarly findings are found throughout most of the world. Recent studies (e.g., Cook *et al.*, 2015) are also suggesting that megadroughts over many areas of the world may become highly likely by the end of the century. Other studies (IPCC, 2013; Seely & Romps, 2015; Reed *et al.*, 2015) suggest that severe storm events are likely to become more intense.

7.5 Alongside the development of climate models, impact models that simulate agricultural systems have also been developed. These are usually 'driven' by climate models, in that they take their meteorological conditions from the climate models, but then go on to simulate the complex plant responses associated with the climate conditions, the interaction of this climate with soil conditions, water availability, etc., as well as changes in atmospheric composition, such as CO_2 concentrations, ozone, etc.

7.6 Ongoing increases in computing power have enabled increases in the complexity, spatial resolution, and ensemble size of climate modeling studies. However, at this time, climate model skill is still limited in particular by resolution and ensemble size, although new studies are addressing both of these issues. In practice there is a trade-off between these elements, and the results of climate impacts assessment are contingent on the chosen emphasis (see e.g. Challinor *et al.*, 2009, Garcia-Carreras *et al.*, 2014). The same reasoning applies to the impacts models themselves. Multi-model ensembles of agricultural models have become increasingly common in recent years, and they have proved to be a useful method for producing more robust results (e.g. Asseng *et al.*, 2013, Elliott *et al.*, 2014b, Martre *et al.*, 2015), including detailed projection of the impact of future drought and heat stress on crop failure (Challinor *et al.*, 2010, Deryng *et al.*, 2014).

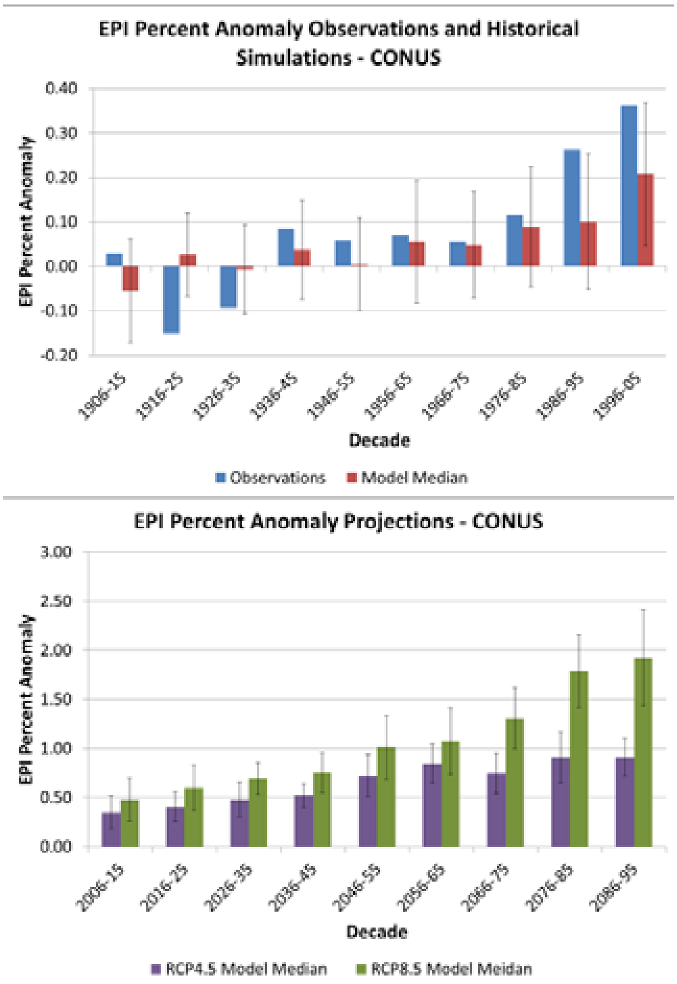

Figure 6: Top panel: Observed decadal (blue) and modeled (red) Extreme Precipitation Index (EPI) percent anomalies for 2 day duration and 1-in-5 year events, percent deviation from long-term mean (1901-1960). The red bars are the median of the CMIP5 historical simulations from 1906 through 2005. The error bars represent +/- 1 standard deviation of the models. Bottom panel: The model median of EPI percent anomalies for RCP4.5 (purple) and RCP8.5 (green) and historical model simulations for the period 1901-2100 by decade. The long term mean is 1901-1960. Error bars show the spread of the models as +/- 1 standard deviation. From Wuebbles et al. (2014).

7.7 Despite the improvements in resolution, and the increased use of multiple agricultural models to quantify and reduce uncertainty, no one modelling system can produce agricultural predictions that are both precise and accurate. Where uncertainty ranges are produced, experts differ on the effectiveness of those ranges in summarising knowledge (Wesselink *et al.*, 2014). Hence, the use of ensembles needs to go hand-in-hand with analysis of fundamental processes, and tools to effectively combine models and data (Challinor *et al.*, 2013). Model-centric and data-centric analysis can be used alongside each other to address uncertainty in adaptation planning (Vermeulen *et al.*, 2013).

7.8 The Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig *et al* 2013) is a distributed program that includes many protocol-driven climate-scenario simulation exercises for historical model intercomparison and future climate change conditions. It involves ecophysiological and agricultural economics modeling groups around the world and includes a number of model intercomparison projects from field to global scale which then form the basis for future climate impact and adaptation assessments. The Inter-Sectoral Impacts Model Intercomparison Project (ISI-MIP; Warszawski *et al* 2014 and Rosenzweig *et al* 2014) takes a similar protocol-driven approach to multi-model biophysical and agro-economic model intercomparison and assessment. The first phase of ISI-MIP, also called the ISI-MIP Fast-Track, expanded the sectoral coverage to include hydrology, biomes, and health impacts of climate change. The agricultural sector, coordinated by AgMIP, included 7 Global Gridded Crop Models (GGCMs) and 9 global agro-economic models, driven by projections for 20 different climate scenarios (4 representative concentration pathways [cite] implemented by 5 different climate models as part of the Coupled Model Intercomparison Project CMIP5 (Taylor *et al*. 2006). In 2013 AgMIP launched the Global Gridded Crop Model Intercomparison (GGCMI; Elliott *et al* 2015) to build on the lessons learned from the Fast-Track model intercomparison. The project is proceeding in three phases: 1) historical model evaluation and validation (2014 and 2015), 2) analysis of the sensitivity of models to Carbon, Temperature, Water, and Nitrogen (CTWN; 2015 and 2016), and 3) a new coordinated assessment of climate vulnerabilities, impacts, and potential adaptations (2016 and 2017).

7.9 Among a number of important outcomes, these projects broadly result in openly available multi-model archives of historical and future crop yield and climate impact simulations, as well as the climatological and agro-environmental forcing data driving these studies. These archives, inspired largely by similar outcomes of the longstanding Coupled Model Intercomparison Project (CMIP) serve to synthesize the best available international science, characterize uncertainties in models and assessment products, and identify key knowledge gaps that must be addressed by the community. We apply these archives here as tools to evaluate the frequency and severity of present and near-future extreme food production shocks.

Changing risk for climate scenarios

8.1 The impact of climate change on future crop production will depend on the impact on mean yields and on the incidence and scale of extreme outcomes. This study also made initial investigation, using the AgMIP/ISI-MIP Fast Track ensemble, into the question of whether risk in regional and global agricultural production is stationary.

8.2 In terms of temperature anomalies, (Hansen *et al*, 2012) show that relative to a base period of 1951-1980, the distribution of temperatures has already shifted to the positive and displays a fatter tail at the warm end of the distribution. (Milly *et al*., 2008) argue that in the context of hydroclimatic change "stationarity is dead" and water resource managers will need to plan for greater uncertainty in flood risk, water supply and quality. In terms of yield projections, (McCarl, Villavicencio, & Wu, 2008) use statistical methods to evaluate the stationarity assumption by first analysing whether climate variables are stationary in the observed data and then using the historical relationship between these variables and yield to project out into the future. Their conclusions do not support the stationarity assumption for future crop yield distributions. (Zhu, Goodwin, & Ghosh, 2011) use statistical methods to show that time-varying models of yield distributions are able to more accurately capture yield risk with important implications for pricing of future agricultural insurance premiums.

8.3 In terms of global calories of maize, soy, wheat and rice produced, the AgMIP/ISI-MIP model ensemble indicates that a 1-in-200 year event given present-day (20th century) climate forcings equates to a loss of approximately 8.5% (Figure 6 top). In fact, according to the ensemble, an event that we would have called 1-in-100 years over the 1951-2010 period could become as frequent as a 1-in-30 year event by the middle of the century.

8.4 This analysis is conducted assuming full effectiveness of CO_2 fertilization effects, but many recent questions have been raised about magnitude of this beneficial effect (Leakey 2009). If we assume instead that CO_2 fertilization effects at this large scale will be completely ineffective, we find similar effects but even more severe in later decades (Figure 5 bottom). In fact, without CO_2 effects, a historically 1-in-100 year event is estimated to occur more than once every 10 years by the second half of the 21st century, and this effect is on top of a large reduction in average yields from climate impacts directly.

8.5 For individual crop/country pairs, the degree of increase in risk over the near-future period can be quite significant. For US maize for instance (Figure 7 top) the 1-in-200 year event in the near future period is 25% more severe than the 1-in-200 even in the historical period (46% loss vs. 36.9%). In this case, what was a 1-in-200 year event in the historical period is comparable to a 1-in-30 year event in just a few decades.

8.6 There are of course some examples where the extreme tail of the distribution improves somewhat, with China/maize as a good example (Figure 8 bottom). Here the ensemble shows marginal improvements in the estimated 1-in-200 year event over the next few decades. The distribution does still shift toward the negative however, with the severity of the 1-in-30 year event increasing nearly 65% (from an 11% to an 18% loss event). Details of the AgMIP/ISI-MIP ensemble for other major crops and producers are included in Appendix B.

8.7 This analysis is very much a 'first look' at how climate change may contribute to a change in the probability of extreme weather driving global production shocks. Caution should be applied when considering the details of the changes outlined here. However, this study does provide some evidence for an understanding of the direction and scale of change of the risk of global production shock events. The simulations clearly indicate that the risk of the events shown in the scenarios is set to increase, both in intensity and severity over time.

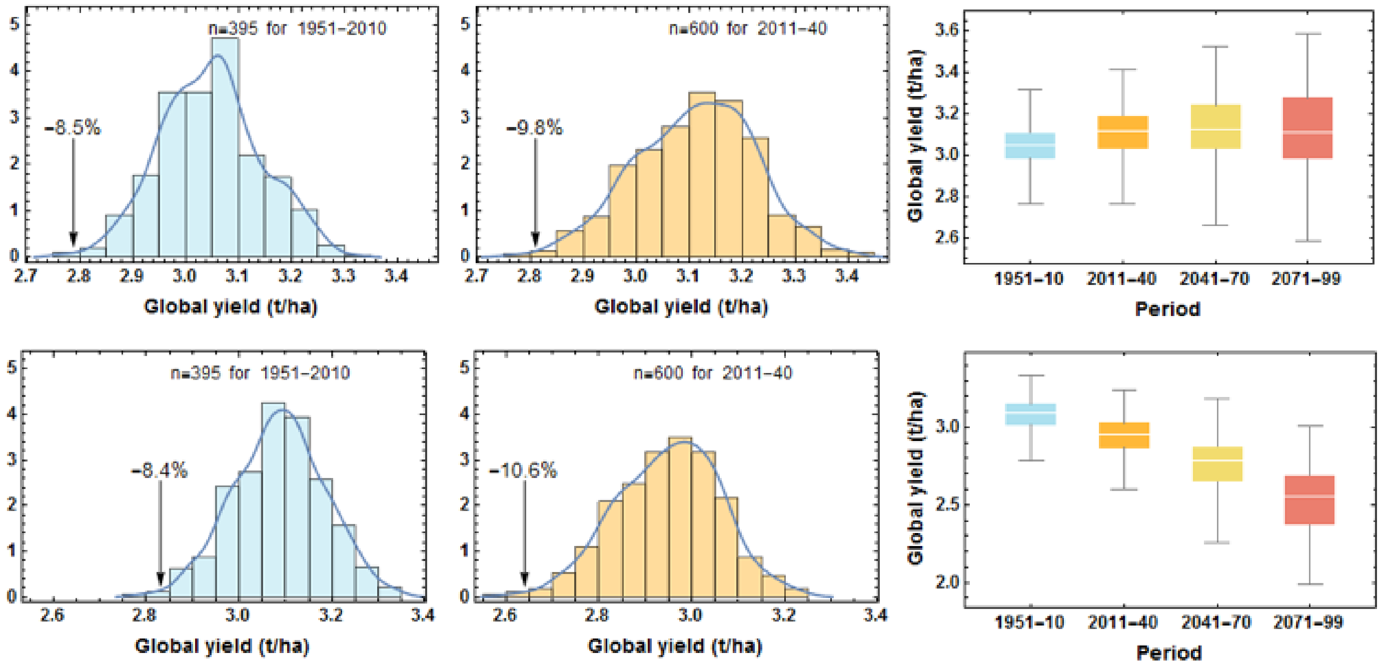

Figure 7: Distributions of global calorie-weighted yield of maize, soy, wheat, and rice for the historical (1951-2010) and near-future (2011-2040) period with (top) and without (bottom) the effects of fertilization from increasing atmospheric CO2 included. The estimated magnitude of a 1-in-200 year event in each period is indicated.

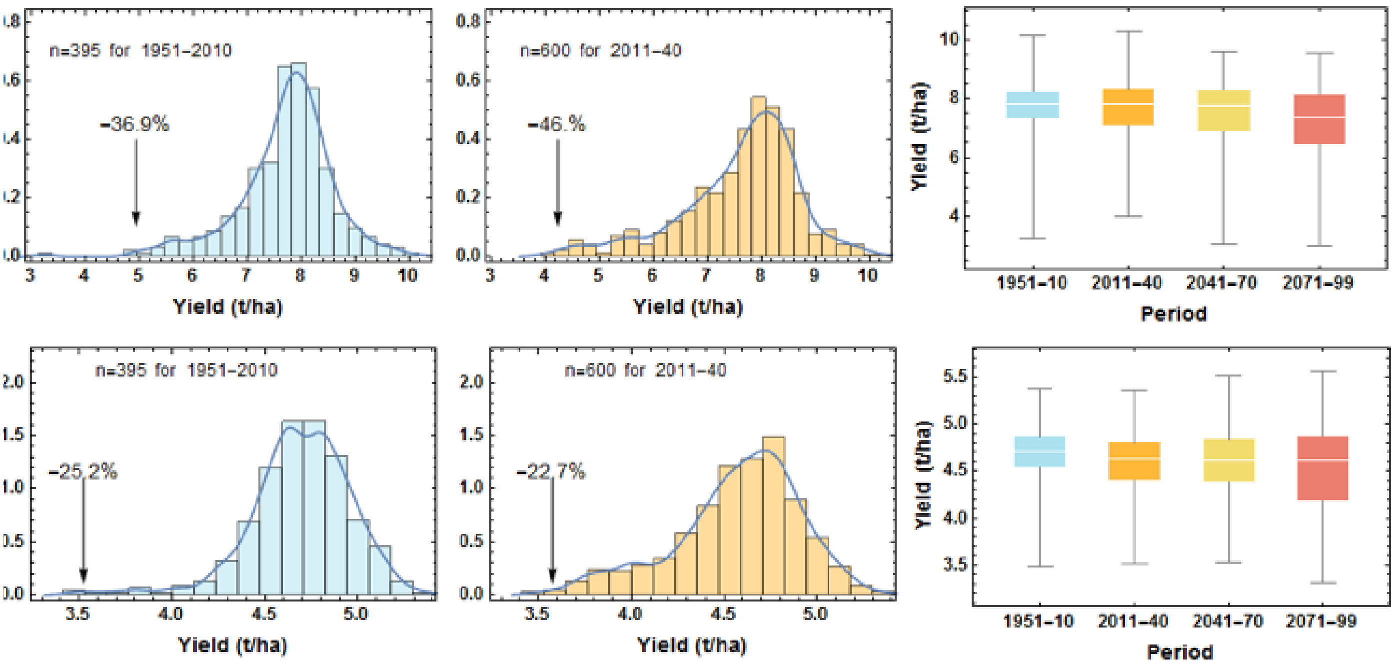

Figure 8: Distributions of maize yield in the US (top) and China (bottom) for the historical (1951-2010) and near-future (2011-2040) period.

Research questions

9.1 The approach documented here is designed to provide plausible scenarios to study the risk of global production shocks and consider how they are likely to evolve over time. However, to fully explore the implications of extreme events in the present and near-future, significantly more research is needed. In addition to generally more in depth analysis, the study highlights the need for many specific steps to advance the understanding of extreme weather risks to global food production. We describe a few of these important research topics here.

9.2 The lack of sufficiently long samples of present day climatology is a major limitation to the quality of the extreme value analysis that can be undertaken. The provision of long simulations of climate under present day forcing (and snapshots of future forcing levels), would allow a more rigorous assessment of the probability of extreme events that could impact on global food production, and therefore a more confident assessment of the level of extreme-event risk in the global food system. That assessment could inform decision making on investments in food security resilience and would form a baseline by which to evaluate the change in risk over time as a result of climate change.

9.3 More research is also needed on the risk of coincident extreme weather events in multiple major breadbasket regions. A full evaluation of coincident events is well outside the scope of the present study, however we here present some preliminary analysis of event coincidence based only on the historical record in order highlight the importance of this topic. We use country-level FAO production data to compare the years of positive (negative) production anomaly in each crop, for each country, with the anomaly in other producing countries for the same crop. No account is made for the size of the anomaly, only that one occurred. It is assumed that the mechanisms causing positive and negative yield anomalies are different and so are shown separately. This was done for both yield (tonnes per hectare) and production (tonnes), although only the results for production are shown here. The results for maize are shown in Figure 8, but the corresponding plots for each of the other three crops is included in Appendix C.

9.4 These relationships are essential for the resiliency of the global food system. For example, this initial look at the simultaneous occurrence of production anomalies in major producer countries for maize, indicates that there may be an anti-correlation between China and the US (Figure 9). More often than not over the last 50 years, negative anomalies in the US are associated with positive anomalies in China (and vice versa). Identifying and studying these relationships is an important part of evaluating the stability and resiliency of global food markets.

9.5 Much more work is needed. The present analysis is based on a very limited sample size and doesn't consider the scale of the anomaly or the drivers of coincident events (e.g. climate teleconnections). It is thus not possible to draw definitive conclusions from this 'light touch' analysis, but it demonstrates potential links and highlights the fact that further studies, both into the statistical correlation of events, and the driving meteorological dynamics behind any correlations, are needed.

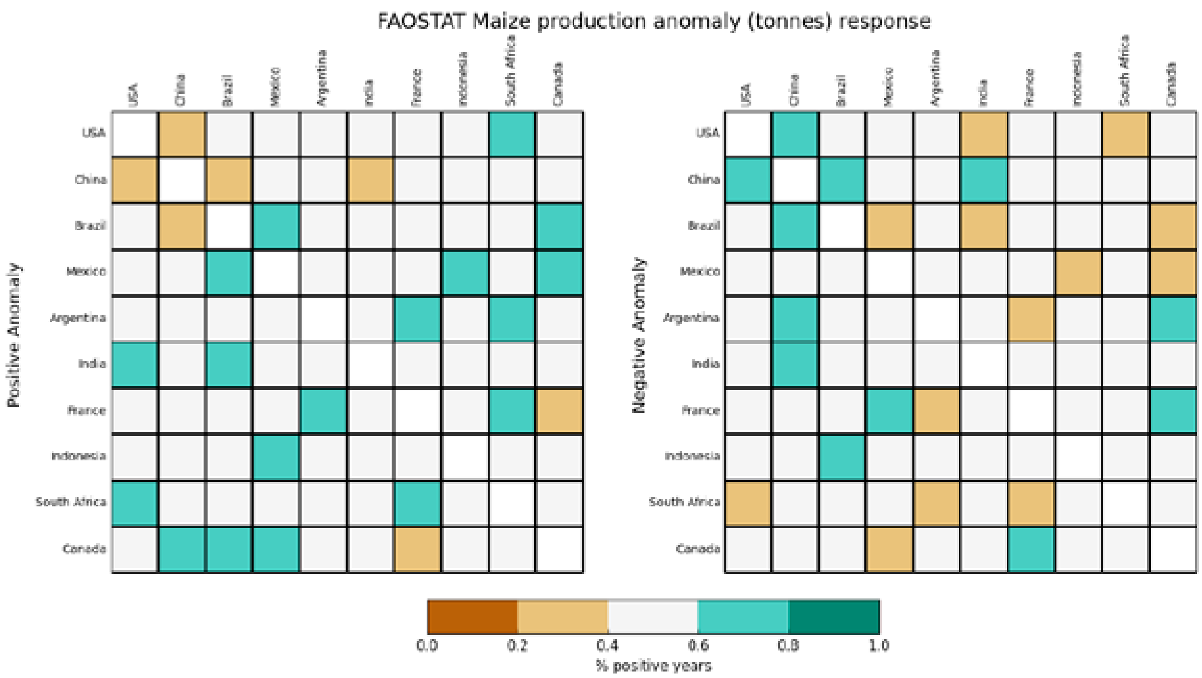

Figure 9: Average production anomalies given a positive (left) and negative (right) anomaly in a major producer (y axis) for 1963-2011, shown in order of size of producer. E.g. left plot shows that for all years in which the US experienced a positive yield anomaly, China experienced a positive anomaly 20-40% of the time (or a negative anomaly 60-80% of the time).

Summary and conclusions

10.1 This study represents an initial look at the evidence available on the exposure and impact of extreme weather events on global food production. The aim was to develop a set of realistic production shock scenarios across the four major global crops (maize, soybean, wheat and rice) that are plausible under present-day or near-future conditions. We conclude that the current global food production system is at risk of shocks from extreme weather, and that this risk is likely to increase over time.

10.2 Production of the biggest global crops (maize, soybean, wheat and rice) is concentrated in a relatively small number of major producing countries, with a large amount of overlap across crops. This concentration exposes the global food system to large shocks driven by extreme weather events in these regions and increases the risk of simultaneous multiple breadbasket failures. However, there is, at present insufficient data available to quantify this risk, either in the present day, or in the future under in a changing climate. There is therefore an urgent need to understand driving dynamics of meteorological teleconnections in order to quantify the likelihoods of coincident production shocks in major food-producing regions.

10.3 By examining the recent past, we see that weather events, particularly drought, are a major driver of lost production. Using the example of past events we generate a set of scenarios of weather-driven production shocks, for each of the four crops, that are plausible in the present or near future climate. These scenarios include production shocks of the order of a 10% decrease in global production for each of the four major crops.

10.4 Climate science research offers the opportunity to explore the implications of climate change for the future risks of food production system shocks from extreme weather, primarily through the use of climate models and crop models. Initial analysis in this study, using crop model data suggests that what we would call a rare extreme food production shock in the late 20th century is likely to become more common in future, and that a 1-in-100-year production loss from the 20th century may be as frequent as 1-in-30 in just a few decades.

10.5 However, estimates of the risks posed by extreme events are currently limited by available model simulations. There is a need for high resolution global climate model runs using stationary present day forcings with ensemble size that are sufficient for probabilistic analysis of extreme event risk. Similar stationary forcing runs for snapshots of future forcing are also needed. Much work is also needed to improve crop model representations of physiological mechanisms, genetic variation and improvement in response to extreme growing conditions. Understanding the interactions between average production increases, variability, and resilience to extreme events is crucial to future food security, and further investigation into the meteorological teleconnections between major food production regions, and the probability of coincident shocks in multiple breadbaskets, both now and in the future, is needed.

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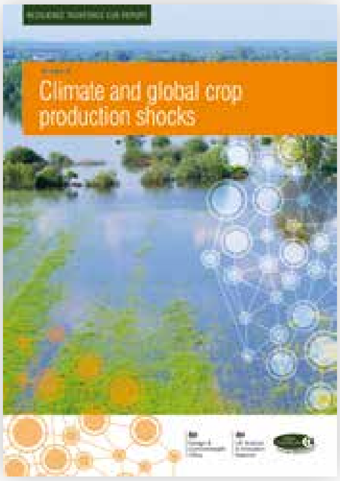

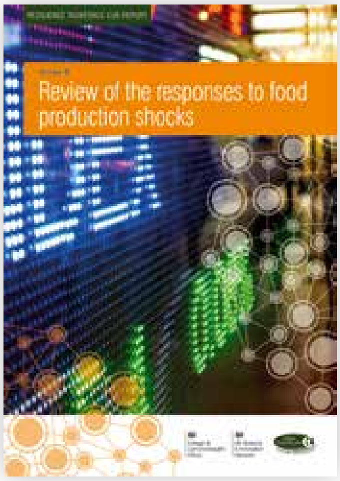

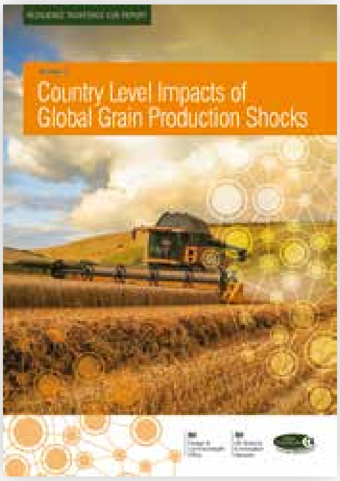

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Appendix A: Scenario development with historical data

Soybean

Geography of production

Similarly to maize, soybean production is focused in a small number of very large producers. In this case the US, Brazil and Argentina, which between them make up around 80 % of global production. The next largest producer is China, with 7 % of the total. Figure 10 shows the geographic distribution of maize production on a world map to illustrate. Although some soybean production is for direct consumption, it is an important global crop mainly as it is the primary source of animal feed globally. The distribution of production indicates that meat production globally has a large dependence on weather impacts on soybean harvests in the Americas, although China, and to a lesser extent India, are also important.

Soybean production has seen an almost tenfold increase since 1960, from around 300,000 tonnes to almost 3 million tonnes (Figure 11). Of the four main crops included in this study, this is the largest rise. It is the result of a combination of both increasing yield and harvested area. This very rapid change over the last 50 years means that it is particularly difficult to assess the impact of weather events on production in the past and compare them with impacts in the present day, or even the near future. In particular the increasing area being planted with soybean now changes the exposure of the crop to weather events, and it may be difficult to identify the weather that has the biggest impact on production as a result.

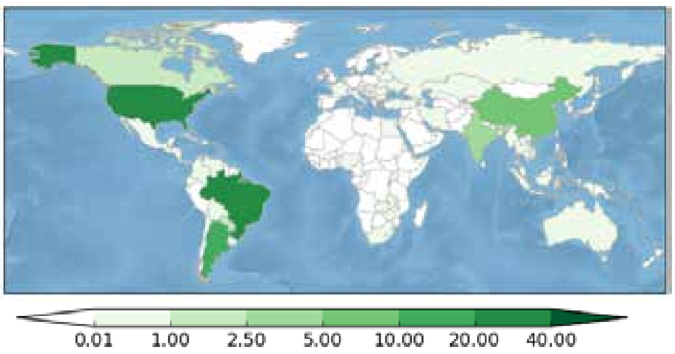

Figure 10: Proportion of total global soybean production grown by country (2001-2010 average). *Source FAOSTAT (2015)*

Historic production shock case study

Since the 1960s there have been a number of large negative soybean yield events including 1974, 1980, 1983, 1988 and 2009. Due to the large change in soybean production during the 60s, 70s and 80s – in which global area harvested increased almost fourfold the low yield events of 1988 and 2009 were assessed. These years provide the best representation of the current soybean production system, and are therefore more relevant.

Unlike for maize, the two selected soybean events show different spatial patterns (Figure 13). In 1988 large yield decreases across North America decreased production in the region by almost 16 % (-8 million tonnes). This was partially offset by positive production anomalies in Argentina and Asia, and resulted in a global production decrease of just over 7 % (-7.2 million tonnes). In 2009 (Figure 12) however, the production anomaly was driven by a large negative yield anomaly in South America. Brazil, Argentina and Paraguay experienced yield anomalies of approximately -0.23 (-8.0 %), -0.78 (-30 %) and -0.96 tonnes per hectare (-39 %) respectively. A small positive yield and area harvested anomaly in the US was not enough to counter these deficits and the global production decreased by over 16 million tonnes (-7.0 %).

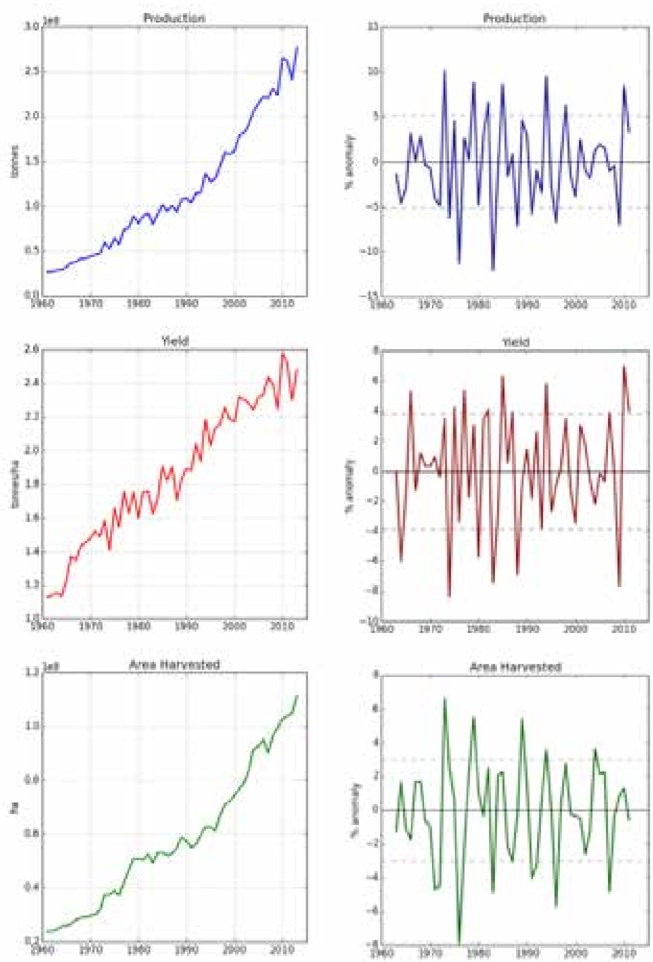

Figure 11: Global production, yield and harvested area data for soybean from 1960 to 2012. *Source: FAOSTAT (2015)*

The physiological requirements for soybean are similar to maize. In the US they are grown in similar regions and have similar growing periods, but with the soybean yield having a greater dependence on the weather in June, July and August (Westcott and Jewison, 2013).

In 1988, the negative yield anomaly in the US is driven by the combination of an anomalously low June rainfall event, followed by above average Jul-Aug temperatures and below average rainfall (Figure 13). These are the same large scale conditions which drove the corresponding 1988 maize yield anomaly, and have been linked to Pacific SST anomalies and local soil moisture conditions (Chen and Newman, 1998).

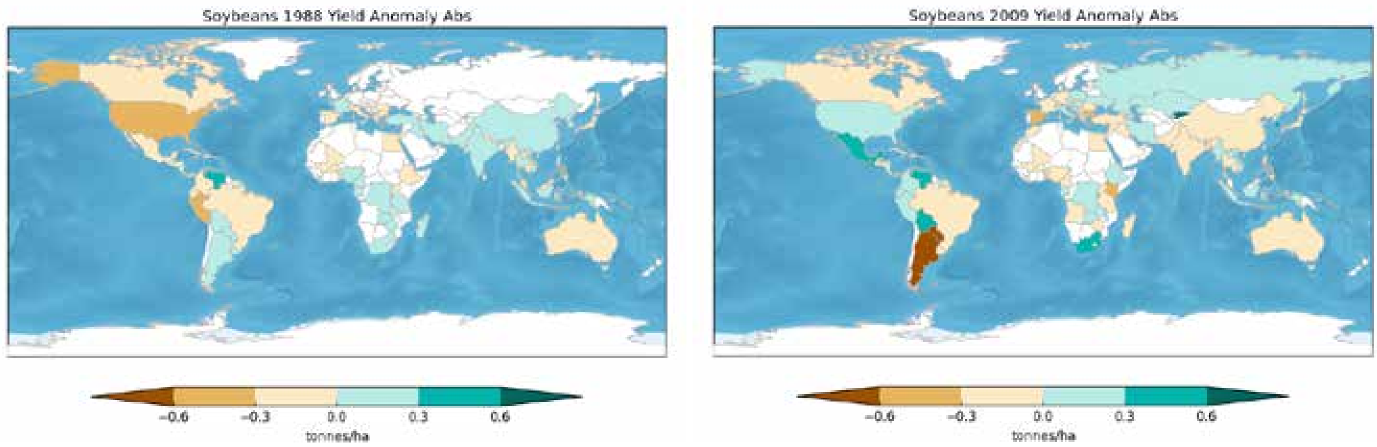

Figure 12: Soybean yield anomalies (tonnes per hectare) in 1988 (left) and 2009 (right). *Source FAOSTAT (2015).*

As in North America, the majority of soybean in South America is rainfed with a single harvest. This increases the vulnerability of the annual yield to severe weather and climatic conditions. The majority of South American soybean growth occurs between December and March. During this period in 2008/2009, the region experienced a severe drought with some areas failing to receive even half of the usual expected rainfall (USDA, 2009). In both Argentina and Brazil - in which the yield anomaly was -30% and -8% respectively - growing season rainfall was down by approximately 200mm and average temperatures were near or above average[1]. These are similar conditions to those driving the US soybean anomaly in 1988.

The drought conditions experienced over South America in 2009 have been linked to a strong La Niña episode (Arndt *et al*., 2010; Chen *et al*., 2010), which began during the last quarter of 2007 and prevailed throughout 2008. The La Niña gradually weakened during the first half of 2009, however the severe rainfall deficit of 2008/2009 had already affected soybean yields across the region. This highlights the increased exposure to severe weather events associated with single cropping practices.

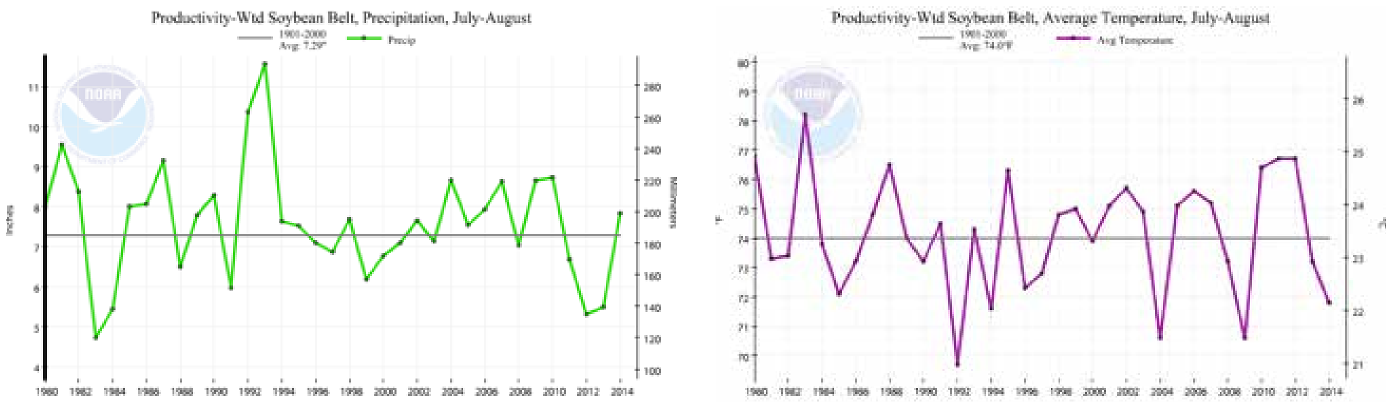

Figure 13: US Soybean Belt July-August precipitation (left) and average temperature (right). *Source: National Centres for Environmental Information (NOAA) (2015).*

1 *Author calculations based on the WFDEI reanalysis dataset (Weedon et al., 2014).*

Production shock scenario

From the data available on the geography of global soybean production, and the examples investigated from the case study year events, the following scenario was developed (Table 4). This outlines representative changes in production levels, based on the actual events of 1988.

Country	Harvest period	% production decrease*	Absolute production loss (tonnes)	Driving meteorology
US	Sept-Oct	17 %	8,351,795	Drought
Brazil	Jan-May	2 %	442,676	
Argentina	April-June	+21 %	1,720,000	
Global		7 %	7234337	

** % of national total*

Table 4: Scenario figures for a soybean production shock (based on 1988 case study)

Notes: For soybean production the severe drought in North America in that year was off-set by high production totals in Argentina, which had optimal weather conditions (positive anomaly shown in orange). Planting in North America occurs in May-June, which is around the same time as the Argentinean crop is harvested. The Argentinean harvest at this time is from the crop planted the previous calendar year. We can therefore rule out the larger harvest in Argentina being a response to higher prices caused by the US harvest failure. It is interesting to note that the Argentinean crop in 1989 is actually slightly down, mainly due to reduced harvested area (which could still be meteorologically driven), even though this crop would have been planted just as the poor harvest in the US was being brought in.

Wheat

Geography of production

Unlike maize or soybean, wheat production has a wide geographic spread. A large number of countries each produce proportionally small amounts of wheat (Figure 14). The largest single producer is China which contributes around 16 % to the global total. This means that wheat production is more evenly exposed to weather events across the globe, and single events, in restricted areas, are less likely to have a large impact on global production. Global wheat shocks are more likely to come from a number of events simultaneously in different parts of the world.

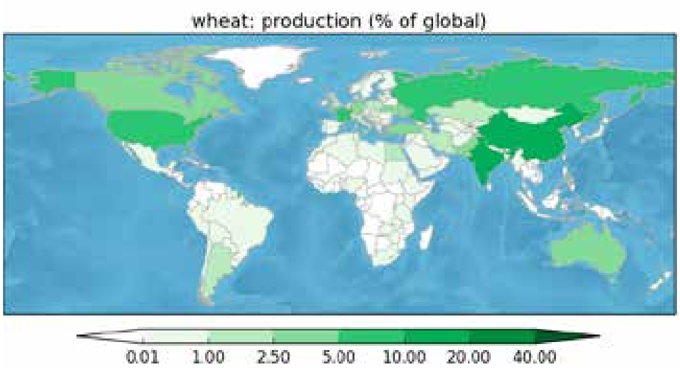

Figure 14: Proportion of total global wheat production grown by country. *Source FAOSTAT (2015)*

Wheat production globally has risen fourfold since 1960, from around 200 million tonnes to around 800 million tonnes (Figure 15). Unlike the other crops in this study, this is predominantly a result of increases in yield. Harvested area has fluctuated over this time, and although it is higher in 2012 than it was in 1960, this change is much smaller than in other crops, and lower than it has been at other times in the past.

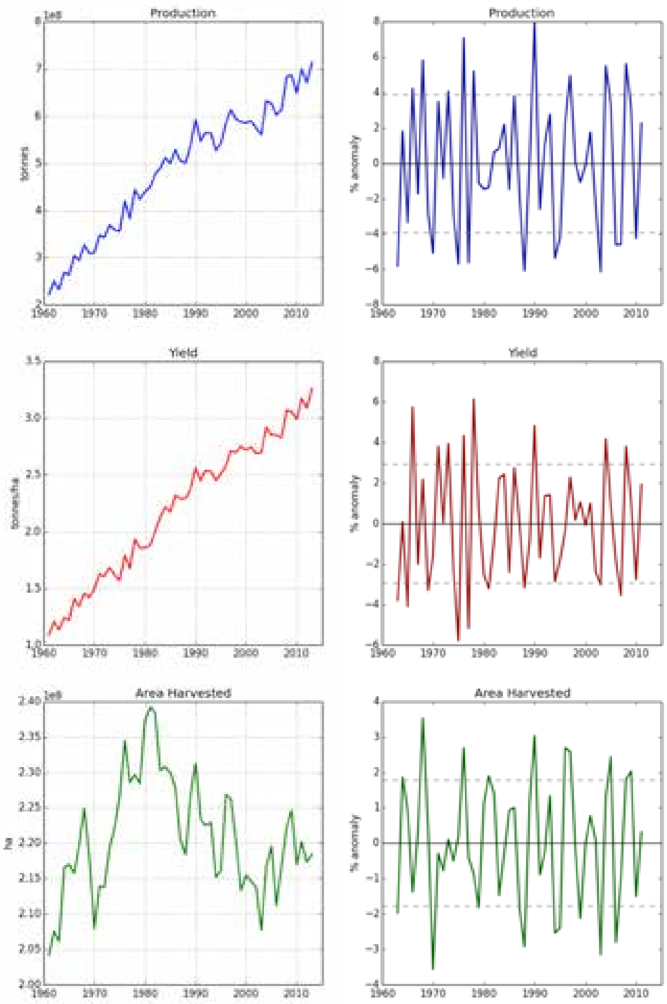

Figure 15: Global production, yield and harvested area data for wheat from 1960 to 2012. *Source: FAOSTAT (2015)*

Historic production shock case study

The production of wheat is spread across a number of countries, ranging from the tropics to the mid-latitude regions; the top 10 producers account for less than 70 % of the global production, with no country producing more (on average) than 17 %. The global wheat yield anomaly time series highlights a number of large negative yield anomalies since the 1970s. To assess events most relevant to present day wheat production, the years of 2003, 2007 and 2010 were investigated.

At the regional scale, a large negative yield anomaly (-9.5 %) occurred across Europe (particularly Eastern Europe, -20.5 %) in 2003 (Figure 16), with an estimated decrease in production of 45 million tonnes (-22%). Combined with a decrease in Russia, this outweighed production gains in North America and Australia, and contributed to a global production decrease of over 35 million tonnes (-6.1%).

As in 2003, Europe and Russia experienced negative yield anomalies in 2007 (Figure 16), however this also occurred alongside negative yield anomalies in the US and Australia. The only top 10 producer to experience a positive yield anomaly in 2007 was Pakistan; although both China and India (the top two producers) had increased production values due to positive area harvested anomalies. These diverse spatial impacts resulted in a decreased global production of approximately 29 million tonnes (-4.6%). The significant production loss has been proposed as a contributing factor to the 2007/2008 price spikes (UK Government, 2010) which had severe impacts on global food security, particularly affecting malnourishment (FAO, IFAD and WFP, 2011).

In 2010 however, the global yield anomaly was not only driven by European countries, but also Russia, Australia and Canada (Figure 16). Yield decreases in China and India of approximately -0.1 tonnes per hectare, and a negative area harvested anomaly within the US resulted in a global production loss of over 28 million tonnes (-4.2%). Whilst both 2003 and 2007 were greater in absolute tonne decreases, in 2010 all of the top 10 major wheat producers (except Germany with a negligible positive anomaly) experienced negative production anomalies. The reduced production led to Russia imposing an export ban; which in turn has been identified as a contributing factor to multiple socio-economic events particularly in Egypt and Pakistan (Welton, 2011).

Based on initial investigations the large decreased wheat production in 2003 appears to have been driven by a number of different meteorological factors. In parts of Eastern Europe, such as Ukraine, which experienced large negative yield anomalies, it has been reported that snow crusting occurred in the late winter and early spring. A warm spell caused the snow to melt. It refroze and formed a sheet of ice which suffocated the plants (USDA, 2004). The yield decreases seen in Western Europe and Russia are instead related to a severe heat wave and drought (Levinson and Waple, 2004) during the spring and summer growing periods. This summer heatwave is also likely to have affected Eastern Europe production. Furthermore, the USDA (2004) reports that weather conditions also affected the area harvested in Europe, China and India; drought or winter-kill meant that some fields were hayed, grazed, or simply abandoned.

To date little work has been done assessing the larger scale meteorological conditions which caused the yield losses in Ukraine, but the 2003 European summer heatwave has been attributed to a persistent upper-level ridge of high pressure centred over the continent, partly related to a prolonged positive phase of the eastern Atlantic (EA) teleconnection pattern (Levinson and Waple, 2004).

In 2007, initial investigations suggest that drought appears to have been the primary cause for wheat production losses in Canada, Australia, Russia and Europe (USDA, 2008b; Levinson and Lawrimore, 2008). In the US, an April freeze and above average annual rainfall contributed to the yield decreases. Torrential rains during harvest period affected Northern Europe (USDA, 2008b). Levinson and Lawrimore (2008) associate the Australian drought to ENSO conditions changing from El Niño to La Niña, whilst the poor conditions in Northern Europe during harvest are associated with a strongly positive North Atlantic Oscillation (NAO).

Unlike 2003 and 2007, 2010 - in which all major producers experienced reduced production – appears to be associated with many different types of weather conditions. Reports suggest droughts impacted Canada and China, whilst Russia experienced a severe heatwave with record high temperatures (Grumm, 2011, Blunden *et al*., 2011). India, which grows wheat during the winter months, experienced a sharp cold spell, whilst heavy rains occurred in Australia during the main growing period (Blunden *et al*., 2011).

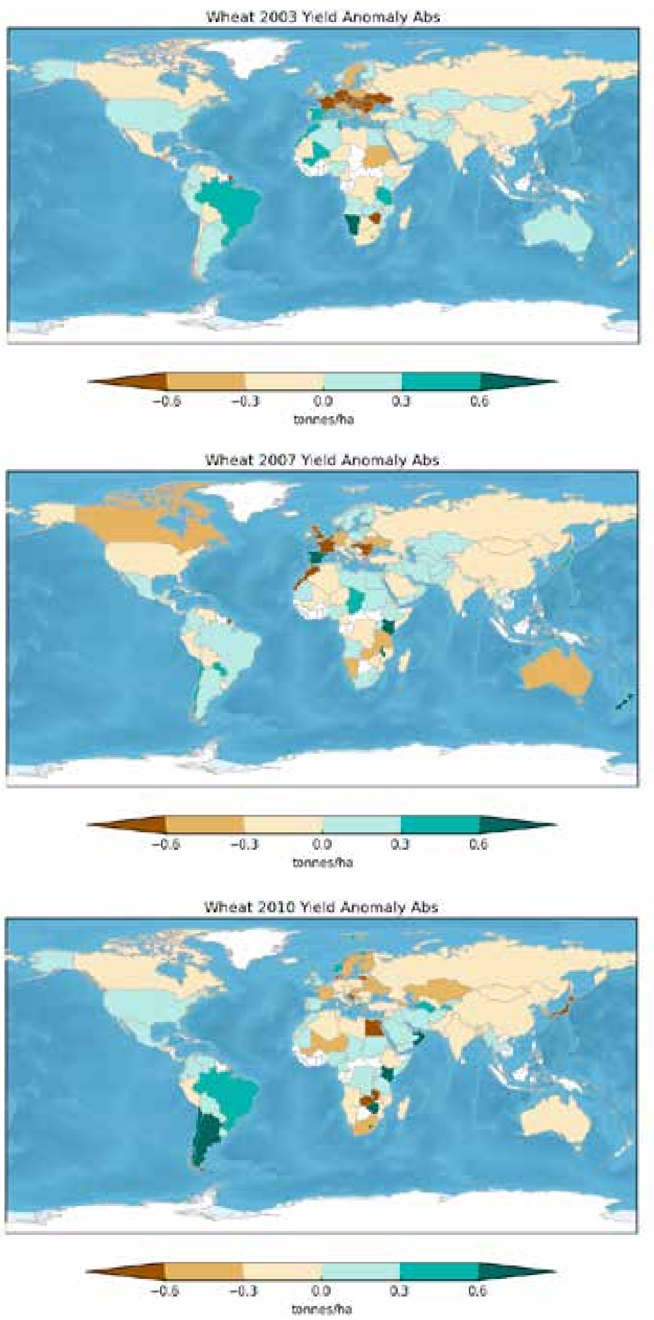

Figure 16: Wheat yield anomalies (tonnes per ha) in 2003 (top left), 2007 (middle) and 2010 (bottom). *Source: FAOSTAT (2015)*

Production shock scenario

From the data available on the geography of global wheat production, and the examples investigated from the case study year events, the following scenario was developed (Table 5). This outlines representative changes in production levels, based on the actual events of 2003.

Country	Harvest period	% production decrease*	Absolute production loss (tonnes)	Driving meteorology
Europe	June-Sept	22 %	45,442,051	Drought, high temps
Russia & Ukraine	July-Aug	38 %	23,602,100	Temporary snow thaw and re-freeze killing winter crop
China	March-June	6 %	5,521,575	
India	March-May	6 %	4,039,420	Failure of monsoon in previous year
Global		6 %	36,588,847	

** % of national total*

Table 5: Scenario figures for a wheat production shock (based on 2003 case study)

Rice

Geography of production

Rice production is primarily focused in South and East Asia, with almost 30 % in China and a further 40 % in India and Bangladesh (Figure 17). Around 20 % comes from Southeast Asia. Rice is a predominantly irrigated crop, but this geographic focus indicates that the relationship between global rice production and the Asian monsoon systems for water availability is likely to be critical.

Global rice production has increased around fourfold since 1960, from around 200 million tonnes to 800 million tonnes per year (Figure 18). This is a result of increases in both yield and harvested area. In many parts of Asia, including China and Vietnam, government initiatives have seen an intensification of production since the 1960s, and multiple crops are grown and harvested in a single year in many locations. This can make it more difficult to identify single weather events that impact on production, but, combined with irrigation, can increase resilience of production to weather shocks.

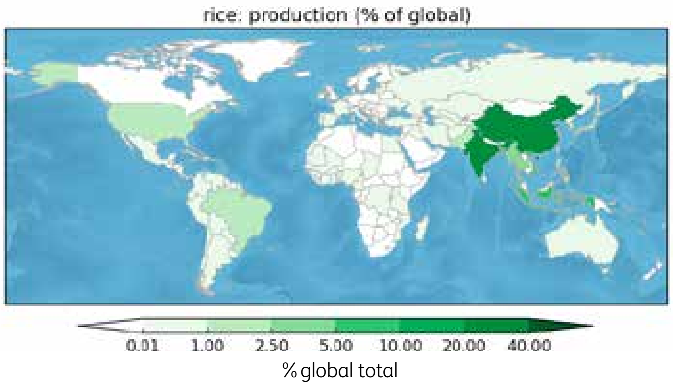

Figure 17: Proportion of total global rice production grown by country. *Source FAOSTAT (2015*

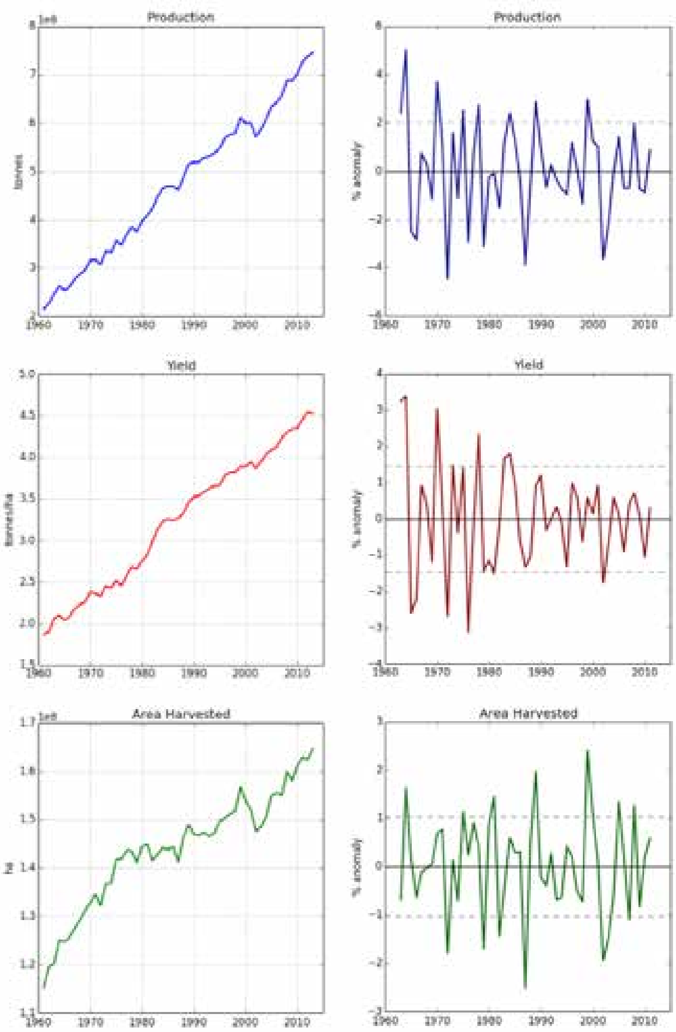

Figure 18: Global production, yield and harvested area data for rice from 1960 to 2012. *Source: FAOSTAT (2015)*

Historic production shock case study

Global rice production is dominated by China and India; together these provide over 50% of all rice production. As seen for other crops, large changes in major producing regions have occurred for rice during the 1960s and 1970s, and thus the use of data from these periods may not be representative of the present day rice production system. For this reason, the years 2002 and 2003 were assessed in more detail; these years provide examples of major production anomalies in both China and India.

During 2002 rice production was reduced by approximately 22 million tonnes (-3.6%) due to negative yield and harvested area anomalies (Figure 19). This was predominantly driven by a negative yield anomaly in India of approximately 10%, although small negative yield anomalies were also seen in China, Bangladesh and Myanmar. In 2003 however it is a large negative production in China of almost 13 million tonnes (-7.8%) – driven by negative anomalies in harvested area and yield – which drove the global anomaly (Figure 19). Positive yield and production anomalies were recorded in India however, at ~4 million tonnes (3.2%), this was not large enough to overcome the loss experienced in China. Other positive and negative impacts at the regional scale largely cancelled out in 2003.

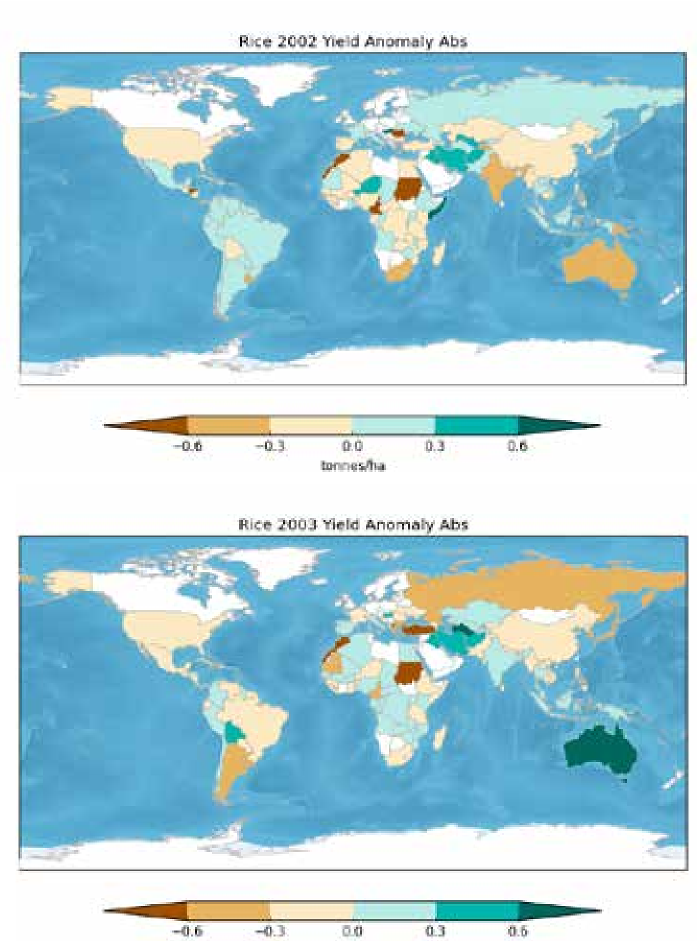

Figure 19: Rice yield anomalies (tonnes per hectare) in 2002 (left) and 2003 (right). *Source: FAOSTAT (2015)*

Within India, the irrigated rice is grown all year round, whilst rainfed lands are grown during June-September, relying on the summer monsoonal rainfall. Due to this, a failure in the 2002 monsoon rains in July (Waple and Lawrimore, 2003) - in which some regions recorded rainfall deficits of up to 76% - is likely to have significantly impacted the rice yield and harvested area (USDA, 2003). This is not the only occurrence of the monsoon failure; Indian production was reduced in 1979, 1982, 1987, and 2009 and these coincide with either a delay or failure of the summer monsoon rainfall.

A number of factors, including Indian and Pacific Ocean SSTs, land-sea temperature gradients and conditions over the Tibetan Plateau, can influence the timing and intensity of the South Asian Monsoon (Turner and Annamalai, 2012). Figure 20 illustrates the relationship between the South Asian Monsoon and ENSO; a number of the observed Indian rice production anomalies have coincided with El Niño events. Furthermore, this could explain observed production and yield anomaly correlations between India and Brazil as El Niño events are associated with drier than average conditions in both regions. Identifying the main drivers is also complicated due to the large amount of rice production which is irrigated in India and China. These systems will rely on different sources for water – monsoon rainfall, glacier melt and ground water, and will affect the vulnerability of local production to weather conditions.

In contrast to the northern regions, south-eastern China, in which most rice is grown, experienced an extended dry spell in 2003 (Lawrimore and Waple, 2004). Some regions received only 65% of the average annual precipitation. The dry spell in south-eastern China also coincided with a July heat wave; combined, these events reportedly killed 30 people and destroyed 1 million hectares of arable land, mostly in Hunan, where 2000 streams and rivers dried up during 2003. There is little literature on the cause of this drought in China, however an important driver of conditions during the summer months is the East Asia Monsoon (Wang et al., 2008) and its role in this event could be investigated further.

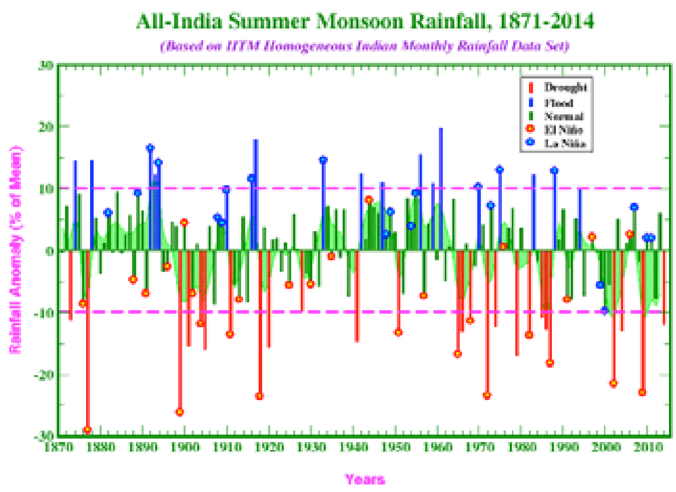

Figure 20: All India monsoon rainfall anomalies and ENSO. Source: http://www.tropmet.res.in/~kolli/mol/Monsoon/Historical/air.html, accessed 25th March 2015.

Production shock scenario

From the data available on the geography of global rice production, and the examples investigated from the case study year events, the following scenario was developed (Table 6). This outlines representative changes in production levels, based on the actual events of 2002 & 2003.

Country	Harvest period	% production decrease*	Absolute production loss (tonnes)	Driving meteorology
China	June-Nov	0.7 %	1,315,410	
India	Oct – Dec	15 %	18,785,959	Failure of monsoon
SE Asia		0.7 %	1,185,531	
Global		4 %	21,729,256	

* *% of national total*

Table 6: Scenario figures for a wheat production shock (based on 2002 & 2003 case study)

Note: 2003 also saw a decline in global rice production (2 %), driven by extreme drought in China. Other regions did not have such a poor year. Combining 2002 rice and 2003 wheat years, which were driven in part by the failure of the same 2002 Indian monsoon, means that this scenario now assumes the failure of the Indian monsoon in two successive years. This is plausible, but is not what happened in these events.

In both the 2002 and 2003 low rice production years, reductions in South America contributed to the global total. The observational evidence doesn't suggest any strong link between Brazil and the US in terms of production anomalies, but meteorologically this does need further investigation to justify the legitimacy of combining years with production shocks in S. America, with other years with production shocks in N. America.

Appendix B: Details of model-based analysis

We consider an ensemble of crop/climate impact models run over an historical period (1949-2007) from the AgMIP Global Gridded Crop Model Intercomparison (GGCMI; Elliott et al 2015), a protocol-based multi-model intercomparison and validation project including 15 global crop modeling groups. We use simulations driven by climate forcing data from the Princeton Global Forcing Dataset (Sheffield et al 2006) and use a skill-weighted ensemble of GGCMI models over the historical period (skills calculated based on time-series correlations between simulated results and FAO statistics at country level). For a detailed description of the GGCMI protocols and models, see Elliott et al 2015.

Model-ensemble-based results

Preliminary results for maize, wheat, rice and soybean are shown in Figures 20-23

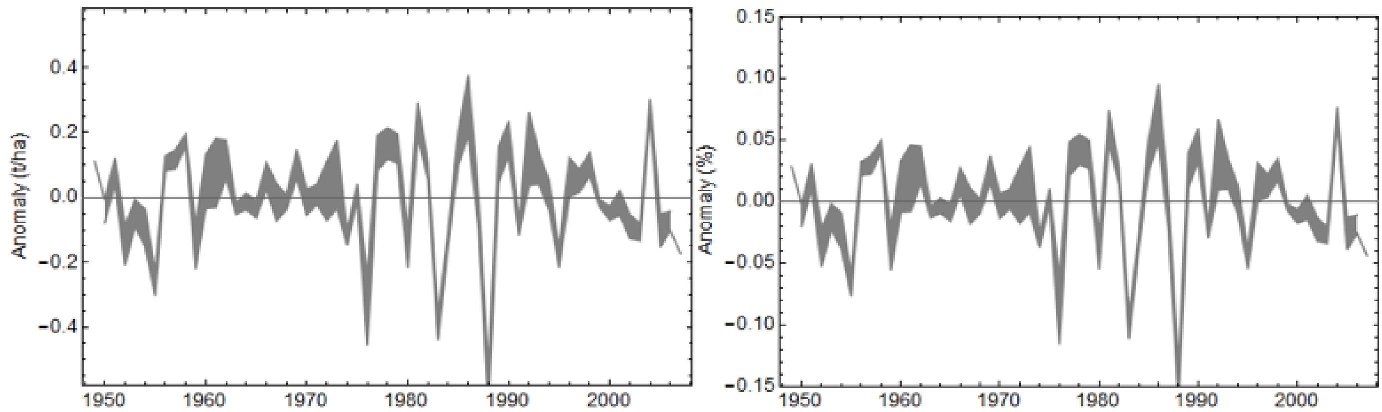

Figure 21: GGCMI model-based anomalies (1949-2007) for global maize production calculated using a range of (equally consistent) detrending and aggregation methodologies.

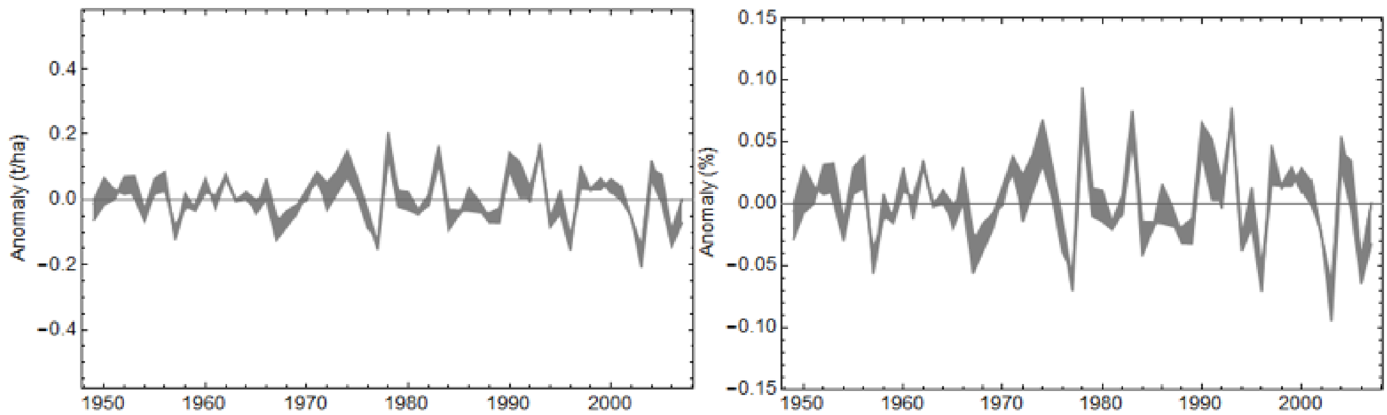

Figure 22: GGCMI model-based anomalies (1949-2007) for global wheat production calculated using a range of (equally consistent) detrending and aggregation methodologies.

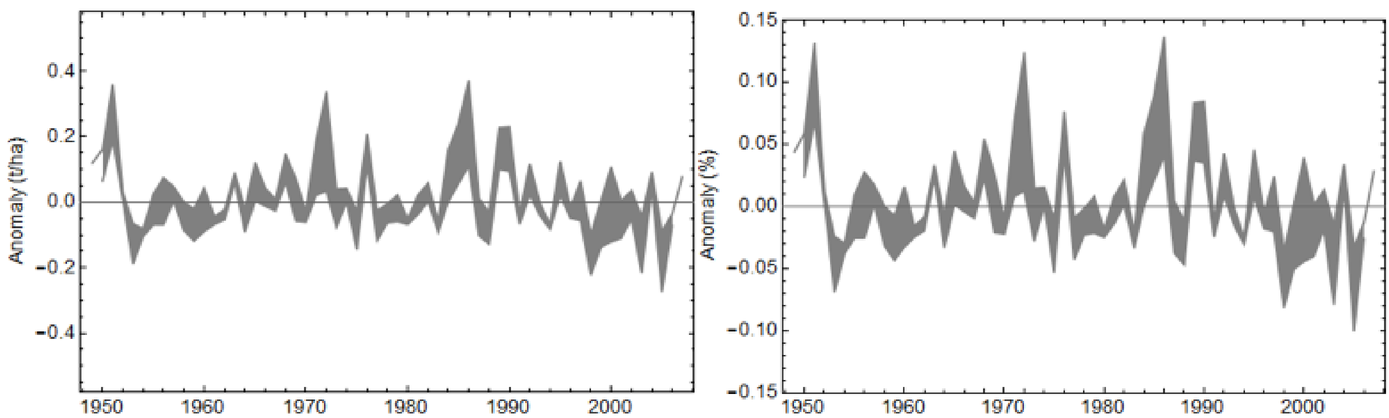

Figure 23: GGCMI model-based anomalies (1949-2007) for global rice production calculated using a range of (equally consistent) detrending and aggregation methodologies.

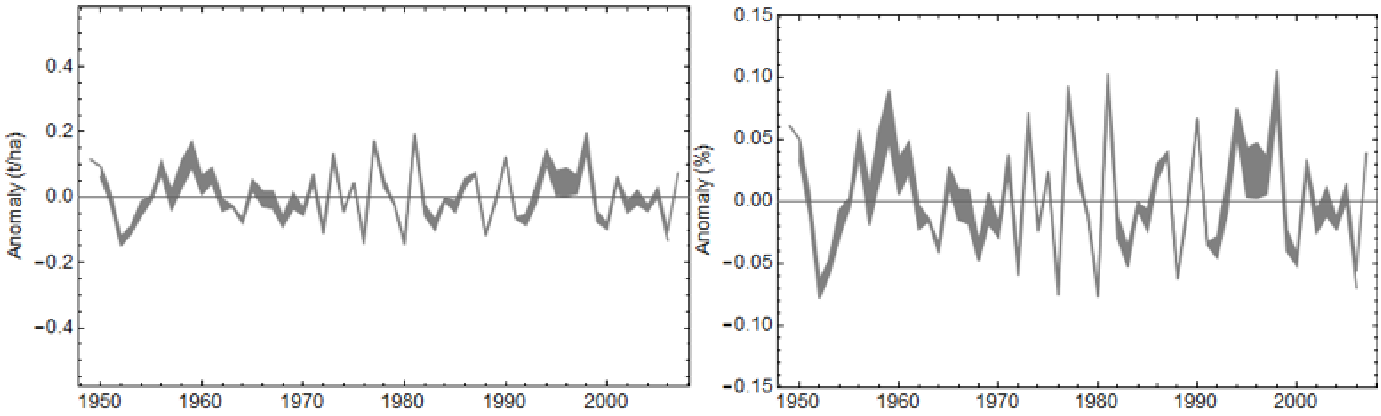

Figure 24: GGCMI model-based anomalies (1949-2007) for global soybean production calculated using a range of (equally consistent) detrending and aggregation methodologies.

Maize

Figure 24 reproduces Figure 7 without the effects of increasing atmospheric CO_2 included.

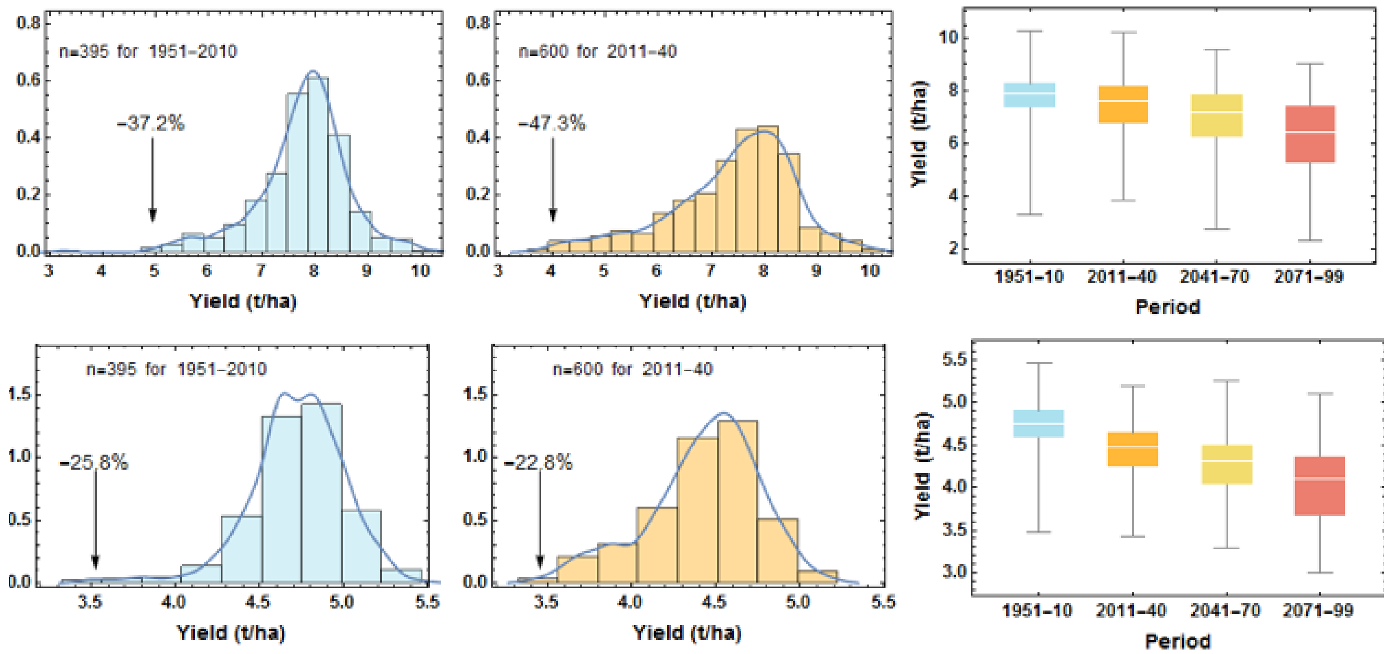

Figure 25: Distributions of maize yield in the US (top) and China (bottom) for the historical (1951-2010) and near-future (2011-2040) period without CO2 fertilization effects.

Wheat

Similar relationships hold for other major crop bread-baskets, such as wheat production in India (Figure 24 - 26), where a 1-in-100 year event in the past is estimated to be approaching a 1-in-30 year frequency by the middle of the 21st century.

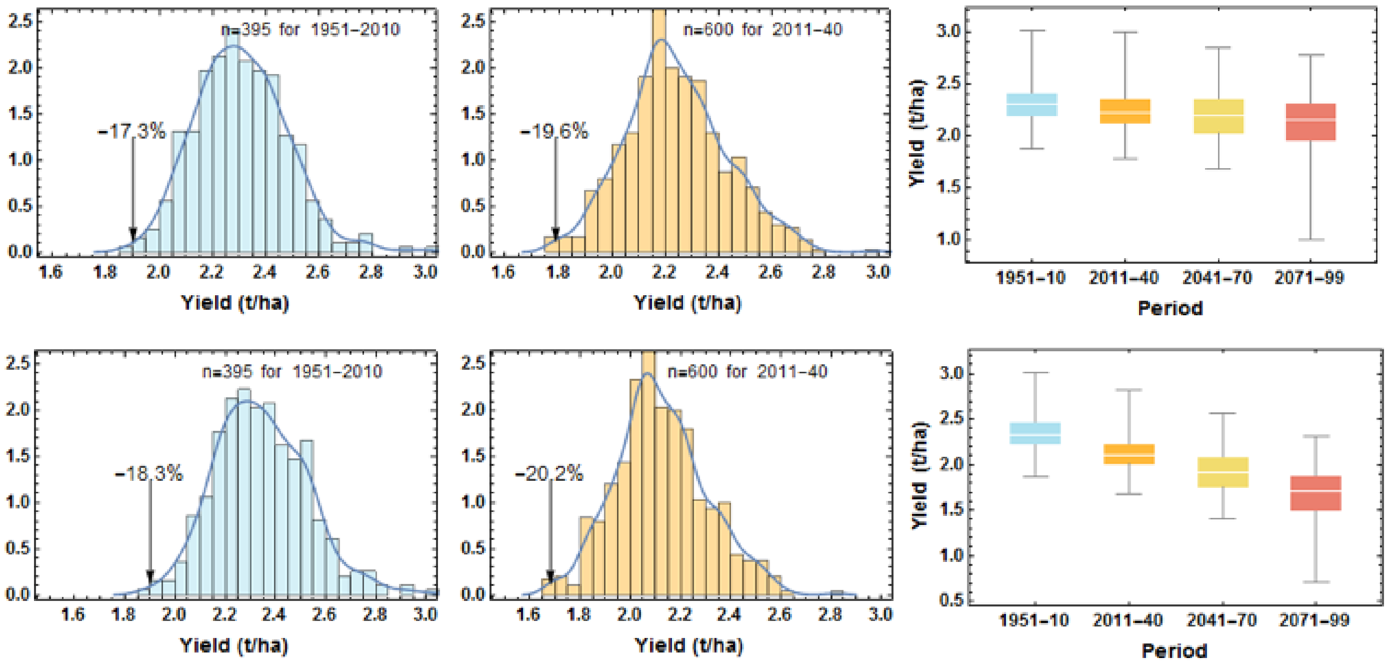

Figure 26: Distributions of wheat yield in India for the historical (1951-2010) and near-future (2011-2040) period with (top) and without (bottom) CO2 effects.

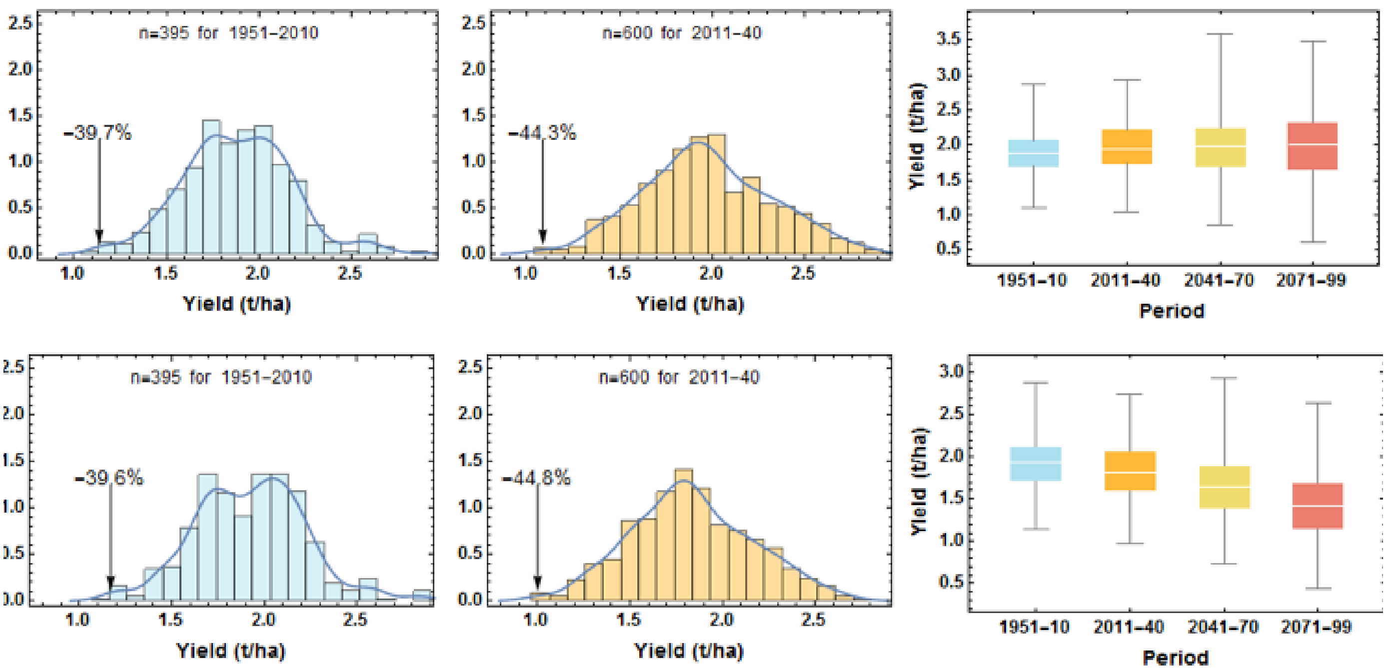

Figure 27: Distributions of wheat yield in Russia for the historical (1951-2010) and near-future (2011-2040) period with (top) and without (bottom) CO2 effects.

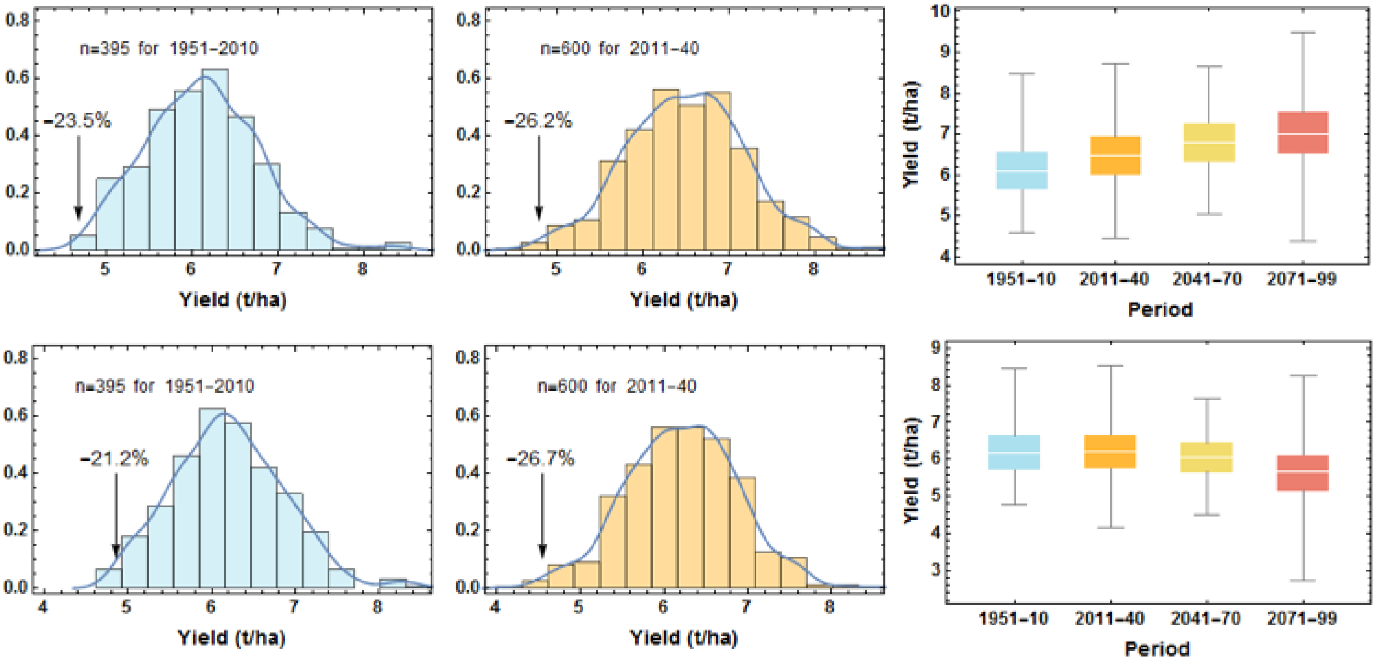

Figure 28: Distributions of wheat yield in France for the historical (1951-2010) and near-future (2011-2040) period with (top) and without (bottom) CO2 effects.

Rice

Rice production in the ensemble shows a more stable risk profile, due in large part to the high prevalence of irrigation and, in the later periods, strong response to CO_2 fertilization.

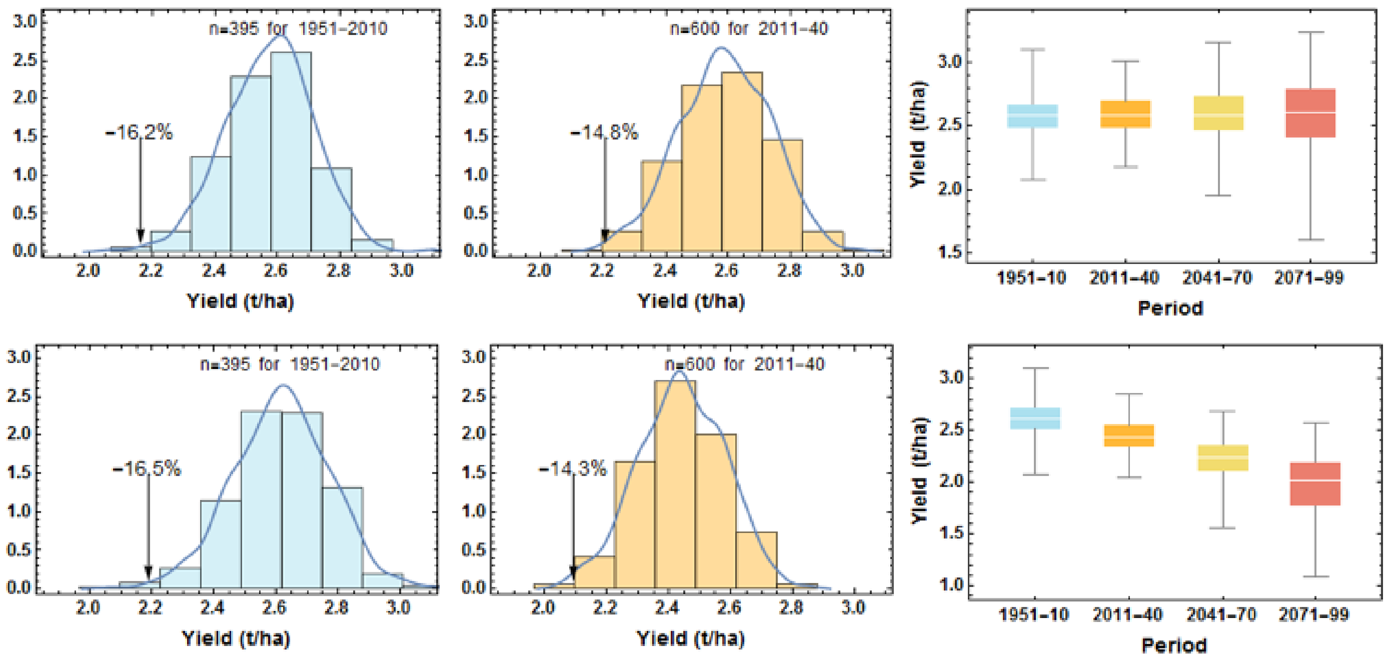

Figure 29: Distributions of rice yield in India for the historical (1951-2010) and near-future (2011-2040) period with (top) and without (bottom) CO2 effects.

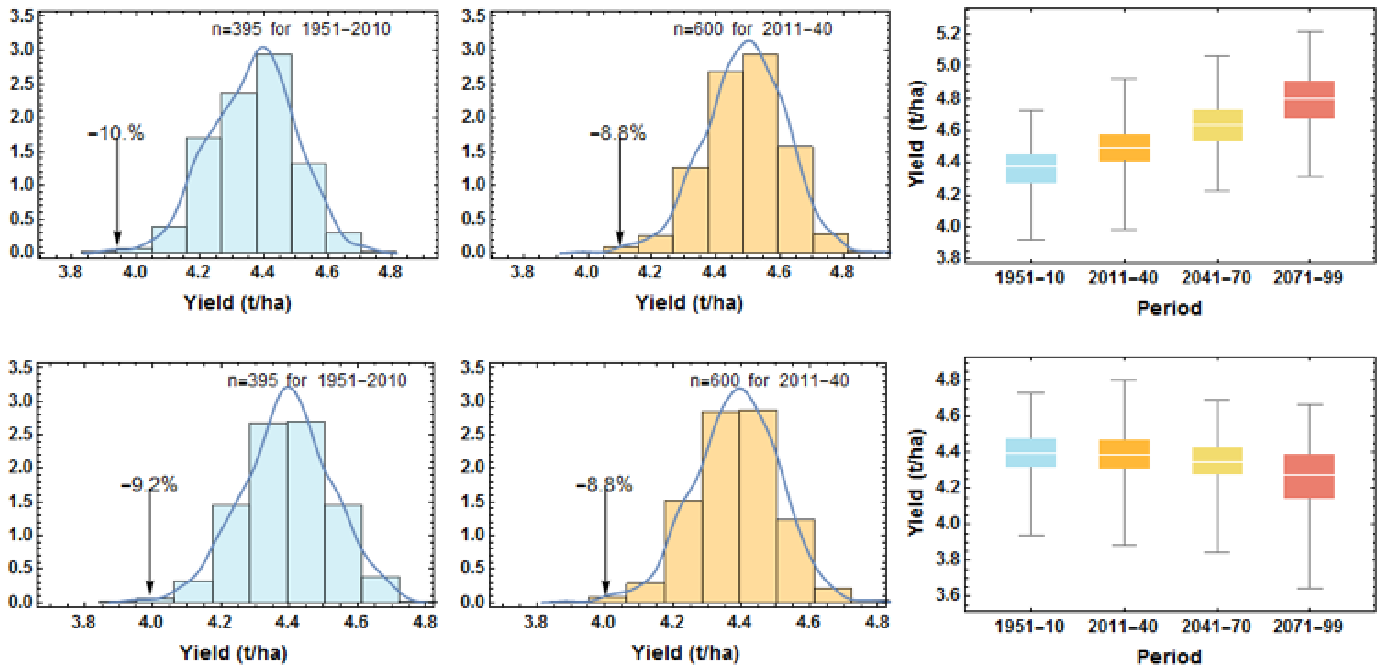

Figure 30: Distributions of rice yield in China for the historical (1951-2010) and near-future (2011-2040) period with (top) and without (bottom) CO2 effects.

Testing against a different crop model

We here consider additional crop models from the AgMIP/ISI-MIP Fast-Track project ensemble in order to check that our basic conclusions hold independent of model choice. We find broadly similar conclusions.

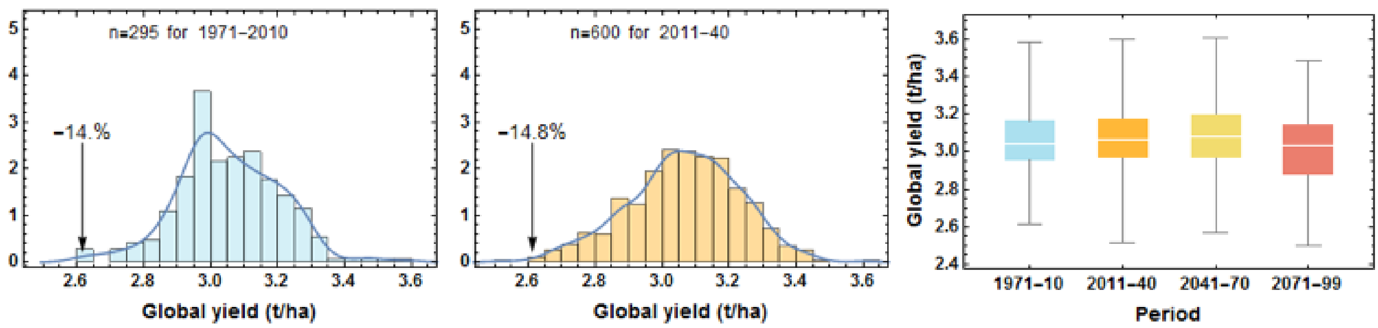

Figure 31: Distributions of global calorie-weighted yield of maize, soy, wheat, and rice for the historical (1971-2010) and near-future (2011-2040) period with the effects of fertilization from increasing atmospheric CO2 included using the GEPIC global crop and climate impact model. The estimated magnitude of a 1-in-200 year event in each period is indicated.

Appendix C: Coincidence of production shocks globally

Soybean

For soybeans, there appears to be some anti-correlation between the US and Brazil (the two largest soybean producers), where a positive anomaly in the US more often corresponds to a negative anomaly in Brazil, and a negative anomaly in Brazil more often corresponds to a positive anomaly in the US (Figure 32). The relationship does not hold in reverse for this data. Again, as with maize, this suggests that there is value in investigating both the statistical coincidence and the underlying driving meteorology of anomalies of production for the major producing countries. In particular the indication that a negative anomaly in China more often coincides with a positive production anomaly in the US is an interesting one, as the kind of relationship could act as a dampener for food security incidents, and should be investigated in more detail.

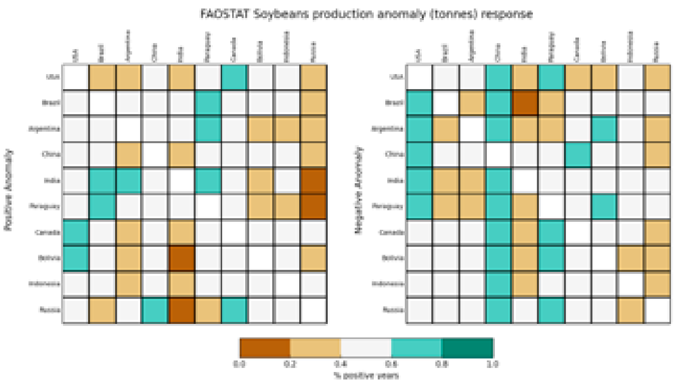

Figure 32: Average production anomalies given a positive (left) and negative (right) anomaly in a major producer (y axis) for 1963-2011, shown in order of size of producer

Wheat

In the case of wheat (Figure 33), although production is widely distributed there does appear to be a potential relationship between production anomalies in the two largest producers, China and India. The historic record shows a correlation of coincidence of positive and negative production events. Whilst this initial look does not provide enough evidence to confirm this relationship, it does support the value of taking investigating further with a more thorough and scientifically rigorous approach.

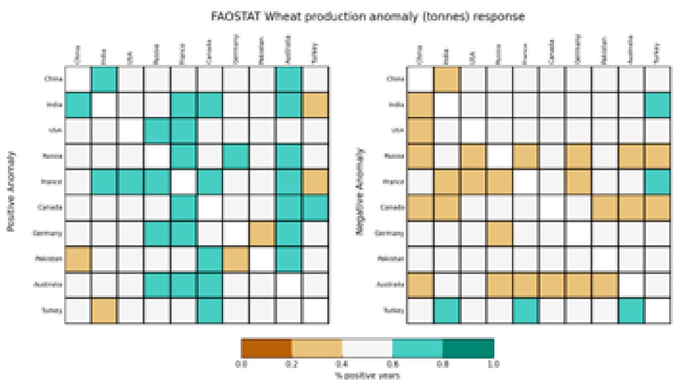

Figure 33: Average production anomalies given a positive (left) and negative (right) anomaly in a major producer (y axis) for 1963-2011, shown in order of size of producer

Rice

Rice production indicates some anti-correlation between negative anomalies in the two major producers (China and India), but no corresponding relationship in the case of positive anomalies (Figure 34). Overall, the data suggests that many of the rice producing countries have good harvests in the same years, but that bad years in one country are more mixed globally. As with the data for the other crops, this is only indicative of possible relationships between different producing countries, and warrants further investigation.

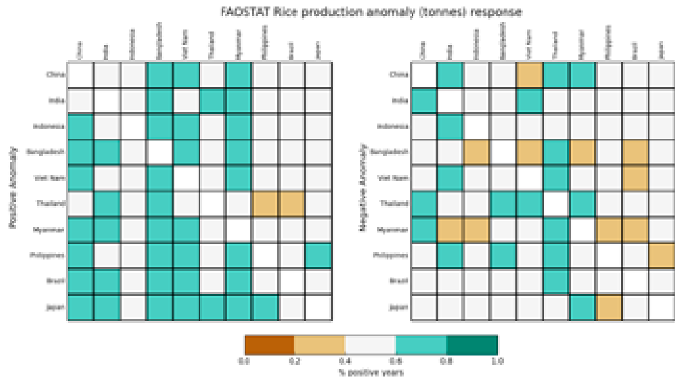

Figure 34: Average production anomalies given a positive (left) and negative (right) anomaly in a major producer (y axis) for 1963-2011, shown in order of size of producer