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Using climate model simulations to assess the current climate risk to maize production

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Abstract
The relationship between the climate and agricultural production is of considerable importance to global food security. However, there has been relatively little exploration of climate-variability related yield shocks. The short observational yield record does not adequately sample natural inter-annual variability thereby limiting the accuracy of probability assessments. Focusing on the United States and China, we present an innovative use of initialised ensemble climate simulations and a new agro-climatic indicator, to calculate the risk of severe water stress. Combined, these regions provide 60% of the world’s maize, and therefore, are crucial to global food security. To probe a greater range of inter-annual variability, the indicator is applied to 1400 simulations of the present day climate. The probability of severe water stress in the major maize producing regions is quantified, and in many regions an increased risk is found compared to calculations from observed historical data. Analysis suggests that the present day climate is also capable of producing unprecedented severe water stress conditions. Therefore, adaptation plans and policies based solely on observed events from the recent past may considerably under-estimate the true risk of climate-related maize shocks. The probability of a major impact event occurring simultaneously across both regions—a multi-breadbasket failure—is estimated to be up to 6% per decade and arises from a physically plausible climate state. This novel approach highlights the significance of climate impacts on crop production shocks and provides a platform for considerably improving food security assessments, in the present day or under a changing climate, as well as development of new risk based climate services.

1. Introduction

In a globalised world the impacts of food production shocks in one country can be felt by millions of people thousands of miles away. Sudden decreases in crop yield in major cereal producing regions of the world, as a result of weather or other factors, have been associated with negative impacts on prices, trade, and food insecure populations (Porter et al 2014, FAO et al 2011, Gilbert and Morgan 2010).

The study presented here explores the risk to global maize production associated with discrete weather events in the present day climate. Using a novel approach, the likelihood of a large yield reduction across the major maize production regions is estimated. The aim is to better understand the climate-related risk of an extremely low production year, in one or more of the major ‘breadbasket’ regions of the world.

Maize is a staple food crop across many regions of the world (Ranum et al 2014), but production is highly concentrated in limited areas of the globe. The United States and China alone accounted for just under 60% of global maize production in 2014 (FAO 2016a), with the majority grown in a small number of states and provinces. Adverse weather conditions in these localised regions could, therefore, have a disproportionately large impact on total maize production and, consequently, maize prices and food security. A wide body of literature has focused on the relationship between maize yield and the climate, making it suitable for a first look at production stability and climate variability.

A significant hurdle to this is the limited number of relevant agricultural and climate observations available. Agricultural production has changed considerably over time (e.g. China’s agricultural reform in 1978, Meng et al 2006), as has the probability of extreme events as the climate has warmed (Bindoff et al 2013). Consequently, information prior to the 1980s has limited value in estimating shocks to present day production. With such a small sample size, it is difficult to statistically distinguish between 1-in-100 or 1-in-10 year return levels in a given region. Furthermore, the spatial component of risk across major producing regions simultaneously cannot be determined from the observational data alone. Nevertheless, understanding the resilience of the global food system to climate extremes remains critically important to global food security planning.

One option explored in this study is the use of agro-climatic indicators with global climate models, which can provide multiple, physically-plausible realisations of the climate (Kirtman et al 2013, Flato et al 2013, Collins et al 2013, Bindoff et al 2013). To quantify the temporal and spatial characteristics of climate-related shocks, it is critical to develop a methodology that captures the main meteorological drivers of the majority of low production events. At the same time, it is important not to add unnecessary complexity that could obscure the key relationships, as well as to make best use of climate model characteristics. For example, the ability of global climate models to provide accurate information on sub-diaily extremes, or highly dynamic features, such as intense rainfall, is limited, whilst their ability to capture large-scale temperature and rainfall patterns is well proven (Kharin et al 2013, Flato et al 2013). If treated appropriately, these models can compensate for limited observational data through improved sampling of natural climate variability (Van den Brink et al 2005).

A range of different meteorological variables have been identified as driving reduced maize yields (Schlenker and Roberts 2009, Lobell et al 2013, Chen et al 2011, Tao et al 2008, Zhang et al 2015); however these are, broadly speaking, proxies for water stress (Urban et al 2013). Here we focus on water stress driven by meteorological drought (Wilhite 2000), since the broad temporal and spatial characteristics align well with the capabilities of climate models (Dai 2011, Flato et al 2013). Unlike previous studies, the agro-climatic indicator developed here uses large-scale observational data to provide a focus solely on large negative yield anomalies, relating to yield reductions of at least −1 tonne per hectare (t ha⁻¹).

In the following sections, the methodology for deriving the water stress indicator is described. The indicator is then applied to 1400 simulations of the present day climate to assess the temporal components of risk at sub-national, national and multi-breadbasket spatial scales, focusing on the United States and China.

2. Methodology

In the United States, six states (located in the ‘Corn Belt’) account for almost 70% of national production (USDA 2016); these include Iowa, Illinois, Nebraska, Minnesota, Indiana and Ohio. In China, the majority of maize is grown in the North East China Plain (Jilin, Liaoning and Heilongjiang), hereafter referred to as NECP, and the North China Plain (Shanxi, Shaanxi, Hebei, Henan and Shandong), referred to as NCP (National Bureau of Statistics of China 2016). Together these provinces are responsible for just under 70% of Chinese maize production. In total, the regions considered in this study (figure 1) account for ∼40% of global maize production.
2.1. Agricultural data

State and province scale maize yield data since 1980, were extracted from USDA (2016) and the National Bureau of Statistics of China (2016). In order to isolate climate-related yield anomalies and remove non-climate factors (Nicholls 1997, Hawkins et al 2013a, Ray et al 2012), yield anomalies are derived through subtraction of the 5 year rolling mean. In all regions there is a long term increase in maize yields, particularly across the Corn Belt (in agreement with Ray et al 2012), but with region specific multi-year variability, both of which can be driven by non-climate factors (Hawkins et al 2013a). Similar results were found using a longer, 11 year window, as well as cubic spline and polynomial regression methods.

The majority of maize in the United States Corn Belt is rainfed, with the exception of production in Nebraska. In contrast, irrigation is much more prevalent across China. In general, the relationship between yield and weather is different for irrigated and rainfed maize (Lobell et al 2013, Butler and Huybers 2015). For this reason, predominantly irrigated areas are not considered in the development of the agroclimatic indicator. Instead, we pool together observations from a larger number of predominantly rainfed states and provinces producing maize, to maximise the sample size (supplementary material available at stacks.iop.org/ERL/12/054012/mmmedia). Time series of maize yields from different agricultural systems were not available for all regions; however, irrigated and rainfed yield anomalies are strongly correlated for regions in the United States (supplementary material). Therefore, whilst the actual yield response is reduced in the highly irrigated areas, the derived indicator can be used across predominantly irrigated regions as a proxy to assess exposure.

2.2. Historical meteorological data

Monthly, area-weighted, 2 metre average temperatures from 1980–2013 were extracted from the Watch Forcing Data Era-Interim dataset (WFDEI, Weedon et al 2014). These are based on gridded observations from the Climate Research Unit (CRU TS3.101/TS3.2, Harris et al 2013), but with discontinuities and outliers removed (Weedon et al 2014). To assess potential observational uncertainty, area-weighted monthly precipitation totals from CRU TS3.101/TS3.2 (Harris et al 2013) and the Global Precipitation Climatology Centre (GPCC v5/v6, Schneider et al 2013) were also extracted for this study. The area-weighted values were extracted from the native 0.5 degree resolution grid for each dataset.

2.3. Severe water stress indicator

Following Urban et al (2015), water stress can be conceptualised into ‘supply’, representing water availability, and ‘demand’, the drying capacity of the atmosphere. The most severe cases of water stress occur during low supply and high demand conditions.

An important implication of this approach is that the indicator will capture the main driver of yield loss, but not other adverse conditions such as flooding, storms or low temperatures, or non-climate factors (Iizumi and Ramankutty 2015, Gornall et al 2010, Chakraborty and Newton 2011). As there is greater confidence in climate models to capture monthly and seasonal conditions compared to daily extremes, seasonal precipitation and temperatures serve as proxies for the supply and demand components. These are selected to coincide with the water-sensitive flowering stage (Urban et al 2015, FAO 2016b), corresponding to June-July-August (JJA) for spring maize in the Corn Belt and NECP, and July-August-September (JAS) for summer maize across the NCP (Meng et al 2006).

The aim of our approach is to identify temperature and rainfall thresholds required to capture yield anomalies such that the yield is reduced by at least 1 t ha$^{-1}$. This represents shocks of approximately 10% and 15% in the United States and China, respectively. To derive statistically robust thresholds we calculate the Heidke Skill Score, HSS (Heidke 1926), for a standard 2 × 2 contingency table which identifies occurrences of threshold exceedences, or not, and occurrences, or not, of large negative yield anomalies. The HSS is calculated for a range of temperature and precipitation values to identify optimal thresholds and to assess uncertainty (supplementary material). The frequency bias, defined as the ratio of the number of threshold exceedences to the observed number of negative yield anomalies (of at least −1 t ha$^{-1}$), is also used as a measure of performance. To ensure that the indicator identifies the appropriate frequency of negative yield anomalies, the bias should be close to unity.

The skill of the Severe Water Stress (SWS) indicator is maximal (≈0.6), and the frequency bias above 0.8, for temperatures greater than 23°C and precipitation less than 250 mm (figure 2(a)), with good agreement between the precipitation datasets (supplementary material). Multinomial re-sampling of the contingency table indicates a range of thresholds that provide statistically similar skill scores (solid black contour on figure 2(a)) with a dependence between temperature and precipitation. Importantly, at these large spatial scales an indicator based on both temperature and precipitation thresholds performs significantly better than when using only one meteorological parameter.

To assess sensitivity to the specific formulation of the indicator, we also consider an indicator constructed by assuming a linear relationship between supply and demand thresholds, SWS$^{S_D}$ (figure 2(b)). The implication being that for a given precipitation total, there is an approximate temperature threshold, above which maize yields are significantly reduced. This is in line with previous studies which highlight the importance of the interaction between temperature and precipitation.
(e.g. Urban et al 2015, Hawkins et al 2013a), but can also be interpreted as a threshold in ‘precipitation effectiveness’ which is often characterised by a ratio between the two variables (e.g. Lang 1920, De Martonne 1926, Thornthwaite 1948).

The HSS and frequency bias values equivalent to the SWS indicator are found when using a slope, m, of 0.028 °C/mm and an intercept, c, of 17.2 °C. Despite the different formulations, the SWS and SWS\textsubscript{lin} indicators (figure 2(c), table 1) demonstrate similar skill in capturing the largest negative yield anomalies, capture sub-samples statistically different from the remaining yields (supplementary material) and are associated with yield anomalies of approximately −1.4 t ha\textsuperscript{−1}.

### Table 1. Severe Water Stress agro-climate indicator definitions. An indicator event is counted if the average temperature (T) and precipitation (Pr) conditions exceed the defined thresholds. The average yields associated with each indicator and each precipitation dataset are provided.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Formation</th>
<th>Average yield anomaly (t ha\textsuperscript{−1}) CRU, GPCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>SWS</td>
<td>Pr $&lt;=$ 250 mm, T $&gt;=$ 23°C</td>
<td>−1.46, −1.55</td>
</tr>
<tr>
<td>SWS\textsubscript{lin}</td>
<td>T $&gt;$ = (0.028 × Pr) + 17.2</td>
<td>−1.32, −1.41</td>
</tr>
</tbody>
</table>

### 2.4. Climate model data

To better sample possible climate conditions in the present day, climate model data are taken from the Met Office decadal climate prediction system (Dunstone et al 2016). The simulations are based on the HadGEM3 GC2 (Williams et al 2015) climate model at a high horizontal resolution; 60 km in the atmosphere and ¼ degree in the ocean. The model simulations are initialised in November from 1981 to 2015 (i.e. giving an 8 month lead time), with 40 realisations each year, providing 1400 simulations of the climate over the period (35 start dates and 40 ensemble members). The model simulations provide 40 times more data than is available from observations from the same period. Using initialised climate
Table 2. Estimated annual SWS event probabilities (%). Uncertainty ranges represent the 5–95th percentiles estimated from 10 000 binomial samples for each region. The number of samples for each dataset is 34 (CRU, GPCC) and 1400 (climate model).

<table>
<thead>
<tr>
<th>Location</th>
<th>CRU</th>
<th>GPCC</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iowa</td>
<td>8.8 (2.9–17.6)</td>
<td>5.9 (0.0–11.8)</td>
<td>11.8 (10.4–13.2)</td>
</tr>
<tr>
<td>Illinois</td>
<td>20.6 (8.8–32.4)</td>
<td>17.6 (8.8–29.4)</td>
<td>23.7 (21.9–25.6)</td>
</tr>
<tr>
<td>Indiana</td>
<td>20.6 (8.8–32.4)</td>
<td>20.6 (8.8–32.4)</td>
<td>20.1 (18.4–21.9)</td>
</tr>
<tr>
<td>Minnesota</td>
<td>5.9 (0.0–11.8)</td>
<td>5.9 (0.0–11.8)</td>
<td>7.0 (5.9–8.1)</td>
</tr>
<tr>
<td>Ohio</td>
<td>17.6 (8.8–29.4)</td>
<td>17.6 (8.8–29.4)</td>
<td>15.1 (13.5–16.6)</td>
</tr>
<tr>
<td>Nebraska</td>
<td>17.6 (8.8–29.4)</td>
<td>20.6 (8.8–32.4)</td>
<td>30.6 (28.6–32.6)</td>
</tr>
<tr>
<td>Jilin</td>
<td>0.0</td>
<td>0.0</td>
<td>1.4 (0.9–2.0)</td>
</tr>
<tr>
<td>Liaoning</td>
<td>0.0</td>
<td>2.9 (0.0–8.8)</td>
<td>3.9 (3.1–4.8)</td>
</tr>
<tr>
<td>Heilongjiang</td>
<td>0.0</td>
<td>0.0</td>
<td>0.4 (0.1–0.6)</td>
</tr>
<tr>
<td>Hebei</td>
<td>14.7 (5.9–26.5)</td>
<td>11.8 (2.9–20.6)</td>
<td>24.1 (22.2–26.1)</td>
</tr>
<tr>
<td>Shanxi</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Shandong</td>
<td>2.9 (0.0–8.8)</td>
<td>5.9 (0.0–11.8)</td>
<td>14.3 (12.8–15.9)</td>
</tr>
<tr>
<td>Henan</td>
<td>0.0</td>
<td>2.9 (0.0–8.8)</td>
<td>11.5 (10.1–12.9)</td>
</tr>
<tr>
<td>Shaanxi</td>
<td>0.0</td>
<td>0.0</td>
<td>0.4 (0.1–0.7)</td>
</tr>
</tbody>
</table>

prediction data helps to reduce model biases relative to the use of uninitialized long model control or transient simulations (Thompson et al 2017). However, the 8 month lead time allows the realisations to diverge in both the atmosphere and upper ocean allowing a wide range of plausible dynamical circulation types to evolve—including extreme events that have yet to be observed. We also note that using a dynamical model ensures that the coincidence of high temperatures and low rainfall anomalies are physically plausible and self-consistent, hence enabling the spatial coincidence of events to be assessed.

The climate model is considered to be indistinguishable from observations if both the mean and standard deviation from the observations (1980–2013, CRU precipitation) are within the respective 2.5–97.5th percentile ranges (i.e. 95% confidence level) from 10 000 model bootstraps, each of equal length to the observations (e.g. Thompson et al 2017). For regions in which this condition is not met, model data are adjusted. Seasonal temperature values are adjusted by shifting the mean and scaling the variance to match the observations with precipitation adjusted using a multiplicative method (Hawkins et al 2013b, Hempel et al 2013, supplementary material). This is a standard method for adjusting climate model data; however, it is noted that, as initialised climate model simulations become more widely used within climate services, the implications of adjusting these large model ensembles to limited observations is a key area for future research. The adjustments implemented here have the largest impact over the Corn Belt, where the model is known to have a warm and dry bias in the summer months (Williams et al 2015).

The sensitivity due to the small observational sample is tested through resampling (removing each year) and the bias correction repeated (hereafter termed bias-correction uncertainty). In addition, binomial resampling is used to quantify the ‘counting uncertainty’. The binomial approach applies since we assume that the indicator’s event occurs with probability, P, which is calculated as the number of events divided by the sample size. Using P as the binomial probability of success, we generate 10 000 random sequences of 34 climate conditions (for the observations, 1400 for the climate model output), and re-estimate the probability of success for each sequence, thereby providing a measure of the uncertainty in P due to the sample size. For example, for a given region, if 3 of the 34 observed years exhibit the required threshold exceedences, the estimated event probability, P, is 3/34 ≈ 0.088. The counting uncertainty associated with this probability can be assessed by randomly resampling 10 000 binomial sequences of length 34 with P = 0.088, i.e. B(34, 0.088). This provides an estimated probability range of 0.029–0.18. If the same event probability were based on 1400 values, rather than 34, the uncertainty range becomes 0.08–0.1, as uncertainty in an event probability decreases with increasing sample size.

3. Results and discussion

3.1. Sub-national event probabilities

The annual probability of SWS events across the major maize producing regions is estimated to range from zero to just over 30%, or approximately 1-in-3 years (table 2), and are broadly consistent with previous drought estimates (McCabe et al 2004, Liu et al 2016b). For many regions the climate model-derived probabilities are considerably higher than those estimated from observations, which is based on a much smaller sample size, and which can vary by up to 4% (in absolute terms) depending on the precipitation dataset.

In the NECP, relatively cool and wet summers provide favourable growing conditions and the annual SWS probability is estimated to be less than 5%. These occurrences represent events not seen in the
observations, in an area that is becoming an increasingly important maize producing region, both nationally and globally (Meng et al. 2006). In all NCP provinces except Shanxi, the observation-based estimates are significantly lower than the model. Resilience planning and policies based solely on observed events in the recent past may, therefore, considerably under-estimate the true risk of climate-related maize shocks in these regions.

By including a large number of model simulations the estimated counting uncertainty on the probabilities is consistently less than ±2% in absolute terms. In contrast, the comparative observational uncertainty ranges can be ±12%, highlighting the limitation of the smaller observational sample size. The uncertainty due to bias correction is smaller than the counting uncertainty for almost all regions (supplementary material). Event probabilities estimated using the SWSLin indicator, are consistent with these results, except for Shandong, Henan and Shanxi provinces, which are slightly higher (supplementary material). The implication that event probabilities are underestimated when using limited observational datasets is, therefore, robust and not strongly dependent on the precise formation of the indicator.

3.2. National-scale impacts
Understand the spatial pattern of risk across a country represents a significant topic of interest as government policies and adaptation decisions are often taken at the national scale (Ghose 2014). A key benefit of using physically plausible model simulations, rather than empirical estimates, is the ability to assess the spatial component of exposure at different scales (supplementary material). Whilst the results presented here are based only on one global climate model, the meteorological fields are also assessed to ensure there is a physically-based description of the events in the model simulations.

Over the United States the climate model gives a chance of ~20% per decade for all six states to simultaneously experience SWS conditions. This is lower than indicated by the observations, but greater than if assuming independence across all six states. Similar conditions were seen in 1988 and 2012, and resulted in large agricultural impacts with estimated total losses over $30 billion (NCEI 2016, Rippey 2015). The 200 mb geopotential height anomalies, for the simulations which manifest impacts across all six states, agree well with the conditions experienced in 1988 and 1997 (figures 3(a) and (c), Trenberth et al. 1988, Hoerling et al. 2014). The model simulations are associated with negative 850 mb meridional wind anomalies over southern states and the Gulf of Mexico, indicating a weakened low level jet and reduced moisture transport to the interior landmass (Brönnimann et al. 2009). These characteristics provide confidence in the model’s ability to
capture the important atmospheric patterns across the region.

Over the NECP the climate model simulations estimate a probability of 33% per decade for one of the three regions to experience severe water stress. This is consistent with the GPCC observational estimate. However, the climate model also contains simulations in which two or even all three of the provinces experience severe water stress. These are unprecedented events which are not seen within the observational datasets, and are particularly important considering the significant expansion of maize production in the NECP. None of the model’s simulations contained simultaneous events in all five NCP provinces; however, the absence of evidence means that it is unclear whether such a situation is simply very unlikely or physically impossible. At the national scale for China, we find instances of simultaneous impacts across four and five of the eight provinces, neither of which are present in the observation datasets. These simulations are associated with a weakened East Asian Summer Monsoon (negative 850 mb meridional wind anomalies across eastern China, figures 3(b) and (d)), although the lower level dynamics of moisture transport in this region are complex. This is broadly consistent with the conditions observed in 1997 (figures 3(b), Zhao et al 2015), in which national production fell by approximately 15 million tonnes, driven by a yield anomaly of −10% (FAO 2016a).

Consistent results are found when using the SWS_{in} indicator. Whilst the absolute probabilities are slightly higher when allowing higher temperature thresholds with increasing rainfall totals, the uncertainty ranges overlap with those estimated from the SWS indicator.

For each of the Corn Belt, NCP and NECP regions the estimated chance of spatially homogeneous events, i.e. coincidence of impacts (or lack of), are found to be higher than if all state or province events are assumed to be independent and random. It is therefore unlikely for individual states or provinces to be affected independently by the climate, an important consideration when assessing risk at the regional or national scales.

### 3.3. Multi-breadbasket failures

The risk of simultaneous impacts in major maize producing countries, i.e. multi-breadbasket failures, is currently unknown, but of critical importance as it provides a quantitative measure of risk to the global food system. Here we define major impact scenarios as when the SWS conditions occur simultaneously over five or more states in the Corn Belt, one or more provinces in the NECP, and three or more in the NCP and China. These scenarios are broadly based on 1988 and 2012 in the Corn Belt, and 1997 and 2000 in China, and are each estimated to have an annual probability of approximately 5% (supplementary material).

### Table 3. Multi-breadbasket annual probability estimates (%) from 1400 model simulations for events in each region with annual probabilities of approximately 5%.

<table>
<thead>
<tr>
<th></th>
<th>Corn Belt</th>
<th>China</th>
<th>NECP</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>0.1–0.6</td>
<td>0.9–1.9</td>
<td>0.3–0.9</td>
</tr>
<tr>
<td>NECP</td>
<td>0.1–0.4</td>
<td>3.6–5.4</td>
<td></td>
</tr>
<tr>
<td>NCP</td>
<td>0.1–0.5</td>
<td></td>
<td>0.1–0.4</td>
</tr>
</tbody>
</table>

The probability of a major impact event simultaneously across both the United States and China is estimated to be up to 6% per decade, with similar probabilities between the Corn Belt and the NECP or NCP regions (table 3). The SWS_{in} indicator gives slightly higher, but statistically consistent results. Almost all of the national scale impacts over China are associated with water stress across the NCP region, and less than half with the NECP. The model simulations which manifest multi-breadbasket failure scenarios are associated with the large-scale atmospheric patterns seen for individual events in the Corn Belt and China, providing confidence in the model. Despite the increased sample size, the estimated probabilities are in line with those expected if the regions are statistically independent. For example, the chance of severe national scale events in the United States and China due to random chance is estimated to be 1%–4% per decade. Therefore, whilst the large scale climate dynamics give rise to major impacts in these regions, currently, there is not enough evidence to suggest that this risk is enhanced or reduced through climate system teleconnections. This should be a focus area for future research. In particular, model simulations which contain simultaneous events across both countries indicate a possible upper-level wave train (figure 4) which could dynamically link the two regions during the summer months.

### 4. Conclusions

Climate change is projected to negatively impact all aspects of food security (Porter et al 2014). However, a limited observational record greatly reduces the ability to constrain estimates of severe yield losses in major producing regions, including multi-breadbasket failures, even in the current climate. Using a novel approach we quantify the probability of severe water stress across major maize producing regions. A new agro-climatic indicator for severe water stress was developed, taking into consideration limitations of the agricultural and meteorological datasets and characteristics of global climate models, and applied to 1400 simulations of the present day climate. The analysis suggests that climate-related shock events are more likely than if estimated solely from historical data. Importantly, we find that large-scale water stress is physically possible in locations where it has not been observed in the last 30 years. Therefore, adaptation
plans and policies based solely on observed events from the recent past may considerably under-estimate the true risk of climate-related maize shocks in these regions. The probability of large-scale water stress across the United States Corn Belt and China simultaneously is estimated to be as high as 6% per decade and occurs within a physically plausible synoptic pattern.

The assessment here is based on simple threshold indicators, using seasonal climate conditions. A key assumption is, therefore, that the derived climate-yield relationships are still valid over the wider parameter space explored by the climate model. In addition, the approach could also underestimate the annual probability of yield reductions since not all higher-frequency temperature or precipitation impacts will be captured. Finally, it is important to note that the analysis performed here is based on one climate model and, thus, provides no assessment of model structural uncertainty (e.g. Knutti et al 2010). In the future, these limitations could be partly addressed through the use of additional climate models and combined with process-based crop models for comparison (e.g. Liu et al 2016a).

To the best of our knowledge, this is the first time the likelihood of a multi-breadbasket failure for maize has been quantified and could be combined with impacts modelling to inform policy planning to manage the level of climate-related risk to global food production. This work demonstrates a new approach that can be easily adapted for other regions and crops (e.g. soybean, rice and wheat) with the potential to greatly enhance the information provided by climate change risk assessments.

Acknowledgments

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Figure 4. June-July-August 200 mb geopotential height anomalies (from all ensemble members and years) and absolute wind speeds averaged over the four climate model simulations which exhibit multi-breadbasket failure events.


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