Increase of simultaneous soybean failures due to climate change

Henrique M. D. Goulart[1,2], Karin van der Wiel[3], Christian Folberth[4], Esther Boere[4], Bart van den Hurk[1,2]

[1]Deltares, Delft, The Netherlands
[2]Institute for Environmental Studies, VU University Amsterdam, The Netherlands
[3]Royal Netherlands Meteorological Institute (KNMI), De Bilt, The Netherlands
[4]International Institute for Applied Systems Analysis (IIASA), Ecosystem Services and Management Program, Laxenburg, Austria

Key Points:

- A hybrid crop model (i.e. physical crop model combined with machine learning) is presented, which outperforms the benchmark models
- Simultaneous soybean failures in the Americas under climate change are mostly driven by changes in mean climate
- Changes in climate variability increase country-level soybean failures but such change is not found for simultaneous failures

Corresponding author: Henrique M. D. Goulart, `henrique.goulart@deltares.nl`

Abstract

While soybeans are among the most consumed crops in the world, the majority of its production lies in hotspot regions in the US, Brazil and Argentina. The concentration of soybean growing regions in the Americas render the supply chain vulnerable to regional disruptions. In the year of 2012 anomalous hot and dry conditions occurring simultaneously in these regions led to low soybean yields, which drove global soybean prices to all-time records. Climate change has already negatively impacted agricultural systems, and this trend is expected to continue in the future. In this study we explore climate change impacts on simultaneous extreme crop failures as the one from 2012. We develop a hybrid model, coupling a process-based crop model with a machine learning model, to improve the simulation of soybean production. We assess the frequency and magnitude of events with similar or higher impacts than 2012 under different future scenarios, evaluating anomalies both with respect to present day and future conditions to disentangle the impacts of (changing) climate variability from the long-term mean trends. We find the long-term trends of mean climate increase the occurrence and magnitude of 2012 analogue crop yield losses. Conversely, anomalies like the 2012 event due to changes in climate variability show an increase in frequency in each country individually, but not simultaneously across the Americas. We deduce that adaptation of the crop production practice to the long-term mean trends of climate change may considerably reduce the future risk of simultaneous soybean losses across the Americas.

Plain Language Summary

Soybeans are the main source of protein for livestock in the world. Most of its production is concentrated in regions in The United States of America, Brazil and Argentina. In 2012, simultaneous soybean losses in these three countries due to anomalous weather conditions led to shortages in global supplies and to record prices. In this study we investigate how climate change can affect future events with similar impacts as the one from 2012. We develop a numerical model to establish relations between weather conditions and soybean yields. We use future scenarios with different levels of global warming, and we analyse the soybean losses with respect to present day and future conditions. We find that the number of simultaneous soybean losses similar to the 2012 event increase in the future due to changes in the mean climate conditions. However, simultaneous soybean production losses due to changes in climate variability are not frequent, despite each country showing frequent regional losses. We deduce that if successful adaptation measures are adopted against the changes in mean climate, the future risk of extreme events such as the 2012 may be considerably reduced with respect to a future without any adaptation.

1 Introduction

Globally soybeans form the main source of protein for livestock feed, the second most consumed type of vegetable oil, and are commonly consumed by humans (Hartman et al., 2011). In spite of its global importance, 80% of the soybean production is concentrated in hotspot regions in the United States of America (US), Brazil and Argentina (FAO, 2022). Simultaneous disruptions in these regions have thus considerable impacts on the global supply chain of soybeans, as was observed in the year of 2012. In that year, low soybean yields in all three countries simultaneously led to soybean shortages and high prices on global markets (FAO, 2022; Zhang et al., 2018). Climate change affects the occurrence and characteristics of extreme events in agriculture (IPCC, 2022). Understanding how climate change affects large scale events such as the 2012 offers relevant insights into the risks and challenges that the globalised agricultural system might face in the future.

Adverse weather conditions are common causes of crop failures. Previous studies show crop yield variability is affected by interannual weather variability (Lobell & Field, 2007; Ray et al., 2015; Frieler et al., 2017). Specifically, climate extremes (Lesk et al., 2016; Zampieri et al., 2017; E. Vogel et al., 2019) and multi-variate or temporally compounding events (Zscheischler et al., 2017; Ben-Ari et al., 2018; J. Vogel et al., 2021; van der Wiel et al., 2020; Hamed et al., 2021) have been highlighted as important drivers of crop growth failures. These have been exacerbated by climate change in the last decades (Asseng et al., 2015; Moore & Lobell, 2015; Ray et al., 2019; Iizumi & Ramankutty, 2016; Zhao et al., 2017; Zhu & Troy, 2018; Wolski et al., 2020).

The agricultural sector is expected to be further affected by continued climate change in the future (Lobell & Tebaldi, 2014; Schauberger et al., 2017; Rosenzweig et al., 2018; Xie et al., 2018). Climate change affects both long term trends of mean climate and climate variability (IPCC, 2022). Long term trends, while relevant for impact estimation, can partly be counteracted by adaptation measures (Butler & Huybers, 2013; E. Vogel et al., 2019; Stevenson et al., 2022), but extreme weather events, caused by climate variability, are not easily anticipated (IPCC, 2022). It is thus relevant to disentangle both aspects of climate change when estimating the potential risks of agricultural losses (van der Wiel & Bintanja, 2021).

There are multiple approaches in representing the interactions between weather and crop development, roughly separated in process-based models and statistical models (Liu et al., 2016). Process-based crop models simulate biological, physical and chemicals processes governing crop growth and are driven by weather, soil, and management information to generate simulated crop outputs. A specific category of such models are Global Gridded Crop Models (GGCMs, Rosenzweig et al., 2014). GGCMs cover the entire globe, allowing for the analysis of large scale events like the simultaneous soybean failure of 2012. The second approach to relate weather to crops is through the use of statistical models (Lobell & Burke, 2010). These utilise calibrated mathematical links between weather and crop information. Different statistical methods are used, from simple linear regressions to advanced machine learning methods.

GGCMs are complex, expensive to build and run, and do not represent the crop response to extreme weather conditions well (Schewe et al., 2019; Heinicke et al., 2022). Statistical models are generally simple to build and flexible to use, but do not necessarily follow physics-based processes and their underlying mechanisms can be hard to trace. Therefore, recent studies have proposed a novel approach, in which process-based and statistical models are coupled in a hybrid model. Hybrid models have been shown to outperform the other approaches, and are especially suited for studies assessing the impacts of climate variability and extreme weather conditions (Feng et al., 2019; Shahhosseini et al., 2021).

In this study, we explore how climate change affects extreme simultaneous soybean failures in the Americas, such as the 2012 event. Specifically, we develop a hybrid model to link weather conditions to crops yields and then adopt the concept of impact analogues (van der Wiel et al., 2020; Goulart et al., 2021) to identify events in the future with similar or larger impacts than the 2012 event. We consider different future climatic forcing conditions and assess separately the contribution of trends in mean climate and trends in climate variability in the occurrence of analogues. we analyse two baseline scenarios: one with a static current climate baseline (assuming no adaptation or technological trends to changing mean climatic conditions) and one accounting for the trends in mean climate and crop yield (tacitly assuming a gradual adaptation of crop production in pace with shifting climate conditions). We analyse potential changes in analogue frequency and magnitude and the driving climatic conditions. Results are shown both for the combined production regions (US, Brazil, Argentina) and separately for each individual country to quantify both synchronised and localised crop yield decline information. We determine if the risk of extreme soybean failures across the Americas is changing due to climate change, and which climate change component dominates the change in risk, changes in mean climate or changes in climate variability.

2 Methods

2.1 Study area

This study explored the influence of climate on soybean yields in the major soybean producing countries: the US, Brazil and Argentina. Together, they are responsible for 80% of the global soybean production (FAO, 2022). We considered only rainfed areas to better capture the interactions between climate and crops. We used the SPAM2010 dataset (Yu et al., 2020) to select areas in which at least 90% of the soybean area is rainfed.

2.2 Climate and crop data

To build the hybrid model, we used simulated climate data, simulated yields and observed yields. The simulated climate data was provided by the Global Gridded Crop Model Intercomparison (GGCMI) initiative (Jägermeyr et al., 2021) and the Intersectoral Impact Model Intercomparison Project (Warszawski et al., 2014). They cover both the historical period and future projections, with daily values at 0.5° x 0.5° spatial resolution. The historical run (1901-2015) consisted of the GSWP3-W5E5 dataset, a combination of two global datasets using reanalyses and gridded field observations: GSWP3 (Global Soil Wetness Project Phase 3, Kim, 2017) and W5E5 (WFDE5 over land merged with ERA5 over the ocean, Lange et al., 2021). The projections cover the 2016-2100 period and are based on three global climate models (GCMs): GFDL-ESM4, IPSL-CM6A-LR and UKESM1-0-LL, which are bias-corrected based on the historic climate dataset as described in (Lange, 2019). Among the 5 GCMs available in ISIMIP, we selected these GCMs as they have different climate sensitivities to CO2 concentration increases: low, mid and high sensitivities respectively (Supporting Information (SI) Table S1, Meehl et al., 2020; Jägermeyr et al., 2021). We used forcings from two Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathway (RCP) combinations: SSP1-2.6 and SSP5-8.5. The combination of GCMs and SSPs allow for the estimation of climate risk under 6 different future scenarios (Jägermeyr et al., 2021). More information on the GCMs and SSPs can be found in the documentation underlying the Coupled Model Inter-comparison Project phase 6 (CMIP6, Eyring et al., 2016).

Simulated yields were sourced from the process-based GGCM EPIC-IIASA (Balkovič et al., 2014) using the same input data described above. The GGCM EPIC-IIASA (Balkovič et al., 2014) is a global implementation of the Environmental Policy Integrated Climate (EPIC) field-scale crop model (Williams et al., 1995). It covers the entire world at a resolution of 0.5° x 0.5°. All GGCM runs had CO2 fertilisation effect on the crop yields.

Observed yields from census data were used to train the hybrid model. We obtained the observed yields and harvest areas for soybeans at a county level directly from the national authorities of each country analysed here. Soybean information for the US was retrieved from the US Department of Agriculture (USDA, 2022), for Brazil from the Brazilian Institute of Geography and Statistics (IBGE, 2022), and for Argentina from the Ministry of Agriculture of Argentina (MAGYP, 2022). Observed crop data in Brazil required additional data cleasning (Xu et al., 2021), consisting of removing counties with less than 1% of the county area used for soybean production. We did not see improvements in doing the same for the other two countries. The datasets were resampled to a 0.5° x 0.5° grid to match GGCM spatial resolution using the first order conservative remapping scheme (Jones, 1999). The observed harvest areas were used to calculate production and area weighted average yield values for each country and for the aggregated area across the three countries. For the projections we fixed the harvest areas to the values of 2012 to have a consistent comparison with the 2012 historical event.

2.3 Data processing and dynamic calendar

We obtained from the GCMs daily maximum and minimum temperature, and total daily precipitation. We processed them to generate multiple climatic indices for temperature and precipitation using the Climpact package (Climpact, 2022, list of considered variables in SI Table S2). The yield data and the climatic indices were detrended to isolate the interannual variability and remove the influence of technology, management, and long-term variability. We fitted linear and quadratic polynomials to detrend the time-series for both historical data and projections, and selected the method with least squared errors.

Given the seasonal differences between the regions analysed, we developed a dynamic calendar following Folberth et al. (2019). It is based on the reproductive stage of soybeans in each grid cell, which is the crop stage most sensitive to weather disruptions (Daryanto et al., 2017; Hamed et al., 2021). The dynamic calendar defines for each grid cell a three-month season starting one month before the month in which soybeans reach the maturity date and ending one month after that month. The soybean maturity date was obtained from the GGCMI Phase 3 crop calendar (Jägermeyr et al., 2021). We divided the climatic indices into two groups: temperature and precipitation (Feng et al., 2019; Hamed et al., 2021). In each group, we selected the climatic index with the highest coefficient of determination (R^2) during the three-month season simulated by a Random Forest model (Breiman, 2001).

2.4 Hybrid model development

The hybrid model consists of coupling the outputs of the process-based crop model with the climatic indices obtained in the previous step in a statistical model calibrated on observed crop data. We also added for each grid cell the country label to represent the influence of non-climatic variables in each country (such as management practices, Crane-Droesch, 2018). The statistical model used is a multilayer perceptron (MLP), a widely-used type of deep neural network with applications in multiple fields (Abiodun et al., 2018; Banadkooki et al., 2020; Panahi et al., 2021). MLPs are a network of smaller individual models, called neurons, which are divided in layers. The input layer receives the data, the hidden layers process the data, and the output layer provides the final output. Each neuron has an activation function, which is responsible for processing the data, and associated weights. The weights of the neurons define their importance in the network. We used the Keras package to develop the MLP (Chollet et al., 2015), based on the TensorFlow platform (Abadi et al., 2015). The MLP has multiple hyperparameters to be configured. We tuned them using a grid-search algorithm, in which multiple runs are tested and the best results are stored (the hyperparameters values are shown in SI Table S3).

We compared the output of the hybrid model with the output of the EPIC-IIASA model, a statistical model based solely on EPIC-IIASA and country index (Stat-EPIC), and a statistical model based solely on the climatic indices and country index (Stat-clim). We first measured the scores of each model at the grid cell level on a test set (out of sample corresponding to 20% of the total data) using the statistical metrics: coefficient of determination (R^2), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Then we calculated the sum of errors of each model for the 2012 year to determine which model represents extreme conditions best.

2.5 Investigating the risk of future failures

We adopted the concept of impact analogues to assess the future risk of soybean failures. Impact analogues have been shown to better represent the risk estimation of extreme impact events than weather analogues (van der Wiel et al., 2020; Goulart et al., 2021). Impact analogues (hereafter shortened to "analogues") refer to events with equal or larger impacts than a historical event. The main impact metric (also referred to as soybean yield losses) is defined as the difference between the annual soybean production aggregated across the three countries (in dry matter weight) and the mean aggregated production across the three countries for the climatology. We have taken climatology to be the 2000-2015 period, as it is the period in which soybean harvest area in South America reduced its expansion rate. For each of the future climate experiments, we calculated annual soybean yields, and identified years with larger negative anomaly than observed in 2012, defining them as the 2012 analogues. We also investigated the associated climatic conditions, and the spatial distributions of the analogues to determine how each country contributed to the total yield loss. In addition, we analysed country scale analogues to determine the risk of regional extreme failures.

Projected crop yields reflect a response to changing climatic conditions (both to the long-term changes in mean temperature and available water, and impacts of episodes with anomalous weather conditions). Exploring trends in weather-induced crop failures can be carried out relative to present day growing conditions (assuming no changes in cropping practices and other trends), or relative to mean future climate conditions to isolate changes in climate variability due to climate change (Butler & Huybers, 2013; Stevenson et al., 2022). We explore separately the contribution of trends in mean climate and in climate variability in the occurrence of simultaneous soybean failures by applying two hypothetical scenarios: 1) future yields are defined relative to a present-day reference, which includes the influence of both long-term trends in mean climate and in climate variability. This scenario represents a hypothetical situation where no adaptation to mean climate is pursued, and we refer to it as "no adaptation scenario"; 2) future yields are expressed according to future baselines, so trends in mean climate are not considered. This scenario simulates a hypothetical situation where complete agricultural adaptation to changes in mean climate is achieved, and we refer to it as the "adaptation scenario". The hybrid model was designed to simulate the variability of crop yields, and was applied to the "adaptation scenario". For the "no adaptation" scenario, we added mean trends from the soybean yield projections simulated by the EPIC-IIASA model to the hybrid model outputs. The trends were adjusted so that the initial simulation years mean (2016-2020) were aligned to the climatology to ensure continuity.

3 Results

3.1 Hybrid model performance and simulation of the 2012 event

We selected total monthly precipitation (prcptot, mm) and average daily maximum temperature (txm, °C) to be used in the hybrid model based on their high scores in our tests (SI Table S4) and on results from previous related studies (Goulart et al., 2021; Hamed et al., 2021). The hybrid model outperforms the other models for each of the three metrics considered when the three countries are analysed together (Table 1) and individually (SI Table S5). When evaluating the performance of extreme events, the hybrid model obtains the lowest sum of absolute errors for the 2012 event, with 88% and 22% error reduction with respect to the Stat-EPIC and Stat-clim models, respectively (Figures 1a and SI S1). The addition of direct climatic information to the process-based model output, as done in the hybrid model, improves performance especially on the grid cell scale, indicating a gain in regionalization (more information on SI section S1, Folberth et al., 2012). Therefore, the hybrid model is the most successful model at simulating soybean yields at the grid cell scale and at representing extreme weather. For the year 2012, the hybrid model shows an accumulated loss (negative anomaly) of 21.1Mt with respect to the the climatology (2000-2015). This is due to losses of 7.2Mt in the US, 4.9Mt in Brazil and 9Mt in Argentina (Figure 1b).

Table 1. Out of sample performance of the models for three metrics: coefficient of determination (R2, no unit), mean absolute error (MAE, $(ton/ha)^2$) and root mean squared error (RMSE, ton/ha).

Model	R2	MAE	RMSE
EPIC-IIASA	-6.4	1.336	1.562
Stat-EPIC	0.25	0.395	0.496
Stat-clim	0.66	0.245	0.334
Hybrid model	0.70	0.228	0.314

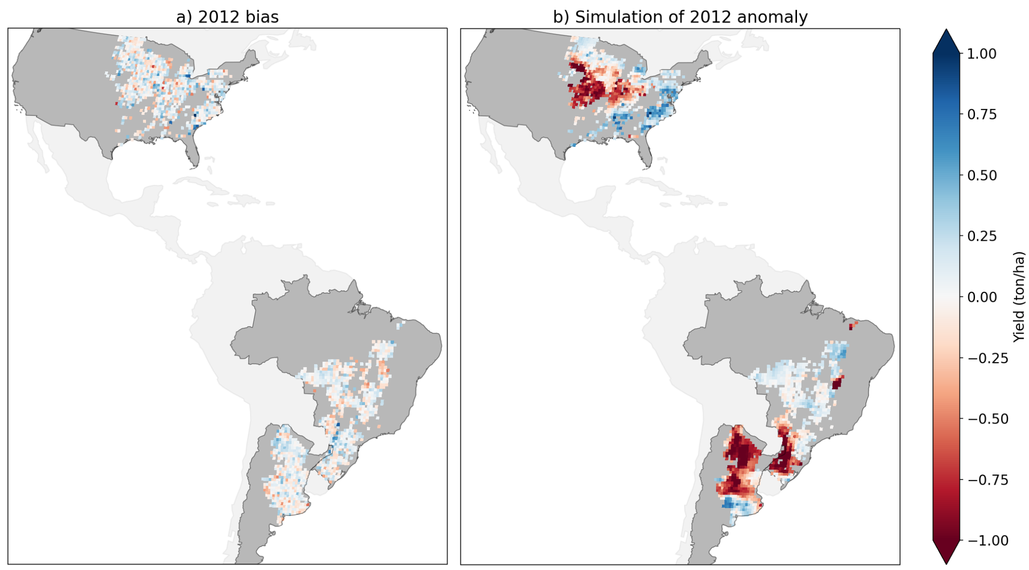

Figure 1. a) Crop yield difference between the hybrid model simulation and the observed data for the 2012 event. b) Simulated yield anomalies by the hybrid model for the year 2012 with respect to the climatology. Results shown in ton/ha.

3.2 Number of future impact analogue events

We investigate the total number of analogue events of the 2012 event for both adaptation and no adaptation scenarios. In the no adaptation scenario the occurrence of analogues is heavily dependent on the future climatic forcing conditions. For SSP5-8.5, a high occurrence of 2012 analogues (82 annual yield values at or below the 2012 yield) is estimated, with mean climatological values of soybean yields crossing the 2012 threshold around the year 2060 in two out of three ensemble members (Figure 2a and SI S2a). For SSP1-2.6, fewer analogues are observed (43), and only one member shows mean climatological values crossing the 2012 threshold. The magnitude of the analogues is also proportional to the forcing conditions, with mean production losses 17% larger than the original event for the SSP5-8.5, and 6% for the SSP1-2.6 (Figure SI S2c). The simulations show that the soybean projections vary across the GCM ensemble members, partly due to differences in sensitivity to increasing CO2 concentrations: the future scenario not crossing the 2012 threshold in SSP5-8.5 is based on the GCM with lowest climate sensitivity to CO2 concentration levels, GFDL-esm4 (Equilibrium Climate Sensitivity (ECS): $2.6°C$), while the scenario crossing the 2012 threshold in the SSP1-2.6 is based on the UKESM1-0-II model, the highest climate sensitivity to CO2 concentration levels (ECS: $5.3°C$, for more information see SI Table S1 and Meehl et al., 2020; Jägermeyr et al., 2021).

The adaptation scenario shows a low number of 2012 analogues (Figure 2b). 9 analogues are obtained in the future scenarios tested, 4 for the SSP1-2.6 and 5 for the SSP5-8.5 (Figure SI S2b). In addition, the changes in losses are not significant, with the SSP5-8.5 and SSP1-2.6 mean losses 2.3% and 2,2% larger than the 2012 event, respectively (Figure SI S2d). The frequency and magnitude of the analogues for the adaptation scenario are significantly lower than in the no adaptation scenario, indicating that the occurrence of future analogues results mostly from trends in mean climate.

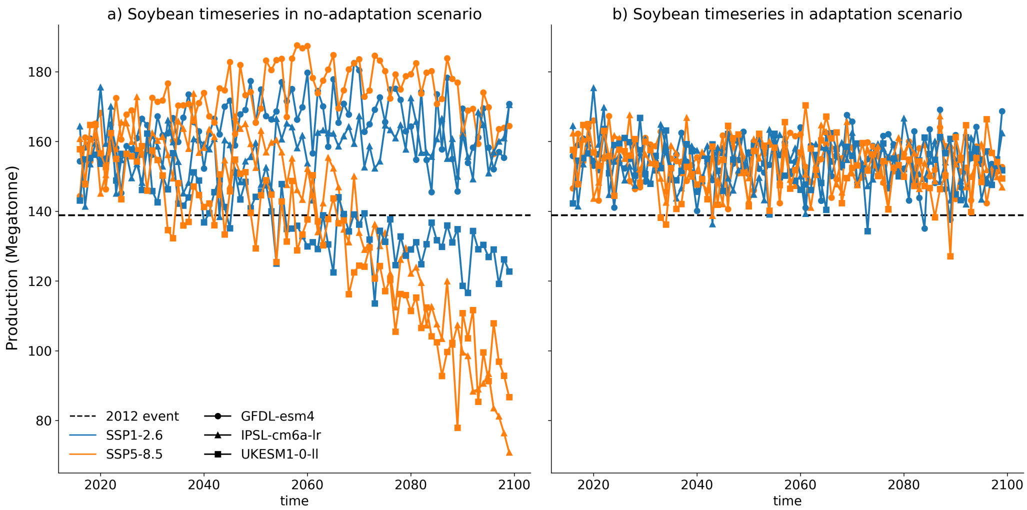

Figure 2. a) Projected soybean yields for the no adaptation scenario. b) Same but for the adaptation scenario. SSPs are defined by colour (blue SSP1-2.6 and orange SSP5-8.5) and GCMs by symbols (circle: GFDL-esm4, triangle: IPSL-cm6a, square: UKESM1-0-II). The magnitude of the 2012 observed event is shown as a black horizontal dashed line. Units are in Megatonnes.

3.3 Impact analogues in adaptation scenario

We run a spatial analysis of the 9 impact analogues in the adaptation scenario to determine the losses in each country. On average, the three countries show production losses with respect to the historical climatology during analogue years (Figure 3). When compared to the 2012 event, analogues losses in the US, Brazil and Argentina increase on average (in brackets the 95% confidence interval) by -1.5Mt (-4.1Mt, 1.0Mt), -0.5Mt (-5.9Mt, 4.8Mt), -0.6Mt(-4.0Mt, 2.8Mt), respectively. Thus, the expected damages associated with 2012 analogues are shown to increase in the three countries when compared to the 2012 event.

We assess the climatic conditions of the impact analogues for the adaptation scenario to check for possible changes in the driving climatic anomalies (Figure 4). The average climatic conditions of the analogues are drier than the 2012 event during the first

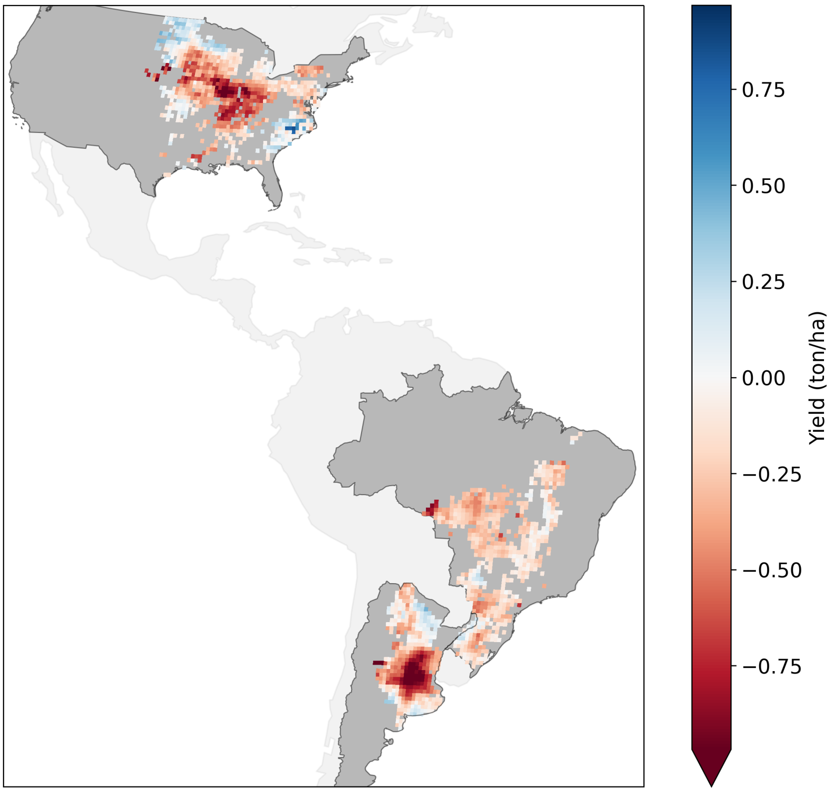

Figure 3. Spatial distribution of soybean yield anomalies in the adaptation scenario averaged across all 2012 analogues compared to the 2012 event. Units are in ton/ha.

and second months of the season, but wetter in the last month of the season. The analogues are on average warmer than the 2012 event during the second and third months, but colder in the first month. With respect to the historical climatology, the 2012 analogues climatic conditions are on average hotter and drier, except for average temperature levels and slightly wet conditions in the third month of the season (Figure SI S3). While the analogues show on average increased hot and dry conditions, we note a significant variability in the climatic conditions leading to these events. It demonstrates the different ways that extreme impacts result from anomalous weather conditions, which highlights the usefulness of impact analogues (van der Wiel et al., 2020; Goulart et al., 2021).

3.4 Country-level analogues

While the simultaneous soybeans failures are the most impactful events for the globalised markets, we also explore the risks associated with soybean failures in each country for the adaptation scenario. We refer to these as "country-level analogues", and they comprise a different selection of years to the aggregated 2012 analogues. The number of country-level analogues of the 2012 event is higher for Argentina (31), Brazil (40) and, especially, the US (84) than the aggregated 2012 analogues across the three countries (Figure 5a). The average losses associated with country-level analogues increase by -2.7Mt (-3.1Mt,-2.2Mt) in the US, -2.5Mt (-3.7Mt, -1.4Mt) in Brazil, and -2.4Mt (-3.2Mt, -1.6Mt) in Argentina with respect to the corresponding country-level losses observed in 2012 (Figure 5b). Therefore, country-level analogues are more frequent than aggregated analogues in the future, and the average losses of country-level analogues increase with respect to

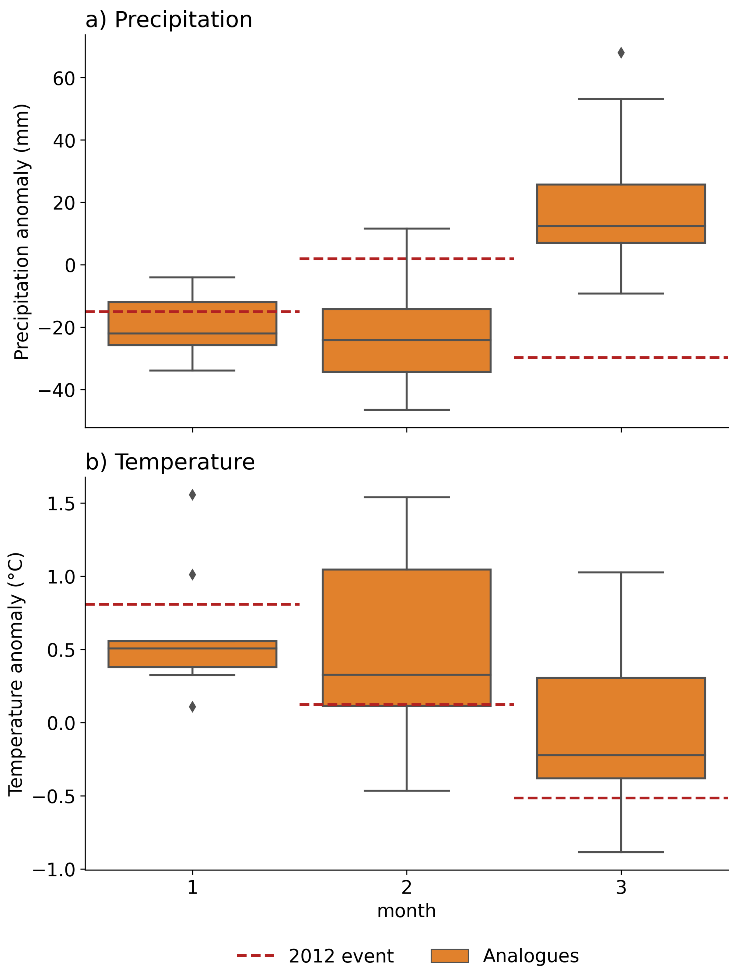

Figure 4. Climatic conditions for the 2012 analogues (in orange) compared with the original 2012 event (red dashed lines). The whiskers denote the distance between the upper and lower quartiles, and the values outside are the outliers (diamonds). Precipitation and average daily maximum temperature values are represented by "prcptot_x" (mm/month) and "txm_x" ($^{\circ}C$), respectively, with x representing the relative month of the season.

the historical 2012 event for all three countries individually. In addition, the US shows the highest number of country-level analogues, significantly higher than the other two countries.

We compare the occurrence of country-level analogues in one or more countries with the occurrence of 2012 analogues (aggregated across all countries) to identify co-occurrences of regional and aggregated soybean failures (Figure 6). The original 2012 event was the result of the three countries having low yields, and we do not identify 2012 analogues coinciding with country-level analogues in all three countries. Instead, 2012 analogues occur due to one or two countries presenting country-level analogues in the same year, but no single country dominates the frequency of 2012 analogues. Our findings highlight the complexity of simultaneous soybean losses across the regions studied, and show that all three countries should be taken into consideration when exploring the global risk of extreme soybean failures.

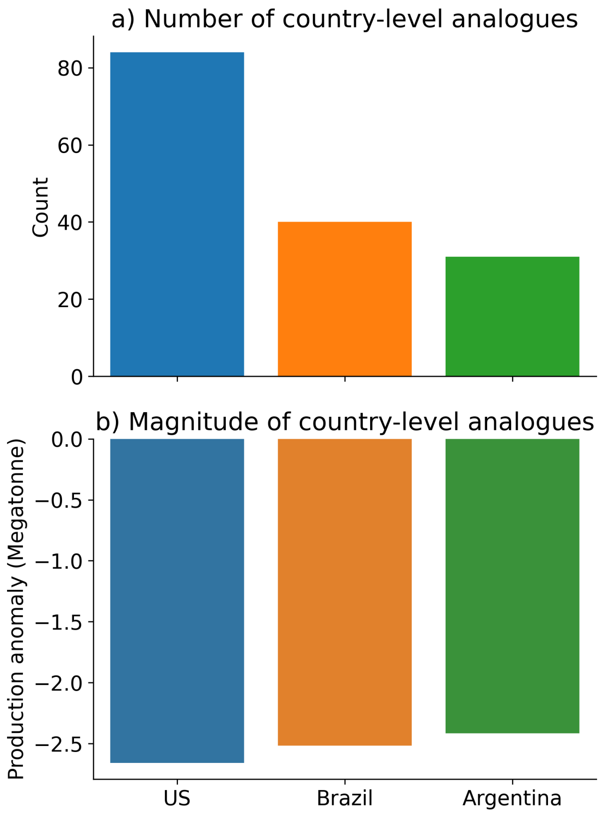

Figure 5. a) Barplots showing the number of country-level analogues per country. b) Barplots showing the average conditions of country-level analogues of the 2012 event for each country. Black vertical lines indicate 95% spread within events.

For each country, we explore the regional climatic conditions linked with the country-level analogues and compare them to the 2012 climatic conditions (Figure 7). The country-level analogues for the US show on average higher temperature levels during the second and third months of the season, but mean wetter conditions during the first and third month. For Brazil, mean temperatures are higher during all three months, and precipitation levels are lower during the first and second months, but higher in the last month. Argentina shows mean warmer conditions in all three months, while precipitations levels are drier for the first and second months. Relative to the historical climatology, the country-level analogues for all countries are the result of hot and dry climatic conditions (Figure SI S4).

4 Discussion

The global agricultural sector is already experiencing adverse effects of climate change (Lobell & Field, 2007), and further impacts are expected in the future due to continued climate change (Jägermeyr et al., 2021). Understanding the possible consequences of climate change on extreme crop failures in the main production areas is of great importance to global food security and the international markets. Soybeans, while globally consumed, are predominantly produced in three countries (US, Brazil and Argentina). Analogues of the simultaneous production failures in these countries as experienced in 2012 were explored under future climate conditions. We used climate model simulations driven

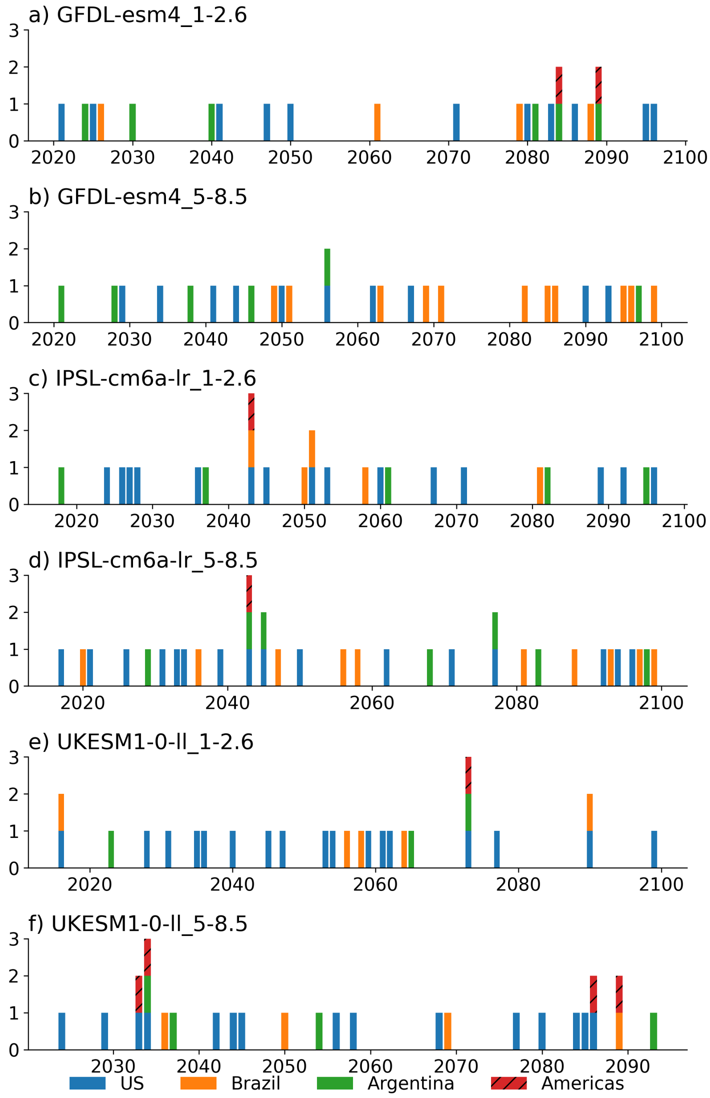

Figure 6. Occurrences of local analogues and simultaneous analogues to the historical event of 2012. Each panel is a combination of GCMs (GFDL-esm4, IPSL-cm6a-lr, UKESM1-0-ll) and SSPs (1-2.6, 5-8.5).

by future emission scenarios and applied a hybrid model the simulate the effects of climate conditions on yields. The hybrid model approach is particularly suitable at the local scale and during years with extreme weather conditions. We adopted an impact perspective (van der Wiel et al., 2020; Goulart et al., 2021), using extreme crop losses rather than climate variables as a starting point of the assessment.

We show that long term effects of climate change are significant. Particularly for high emission levels the occurrence of impacts analogous to the 2012 event increases both in terms of frequency and magnitude of yield anomalies. This is in agreement with other studies (Deryng et al., 2014; Schauberger et al., 2017; Wing et al., 2021; Jägermeyr et al., 2021), which projected lower crop yields in the future as a results of long term mean climatic trends. However, when removing the trends in mean climate and considering only changes in climate variability, our adaptation scenario, the change in analogue fre-

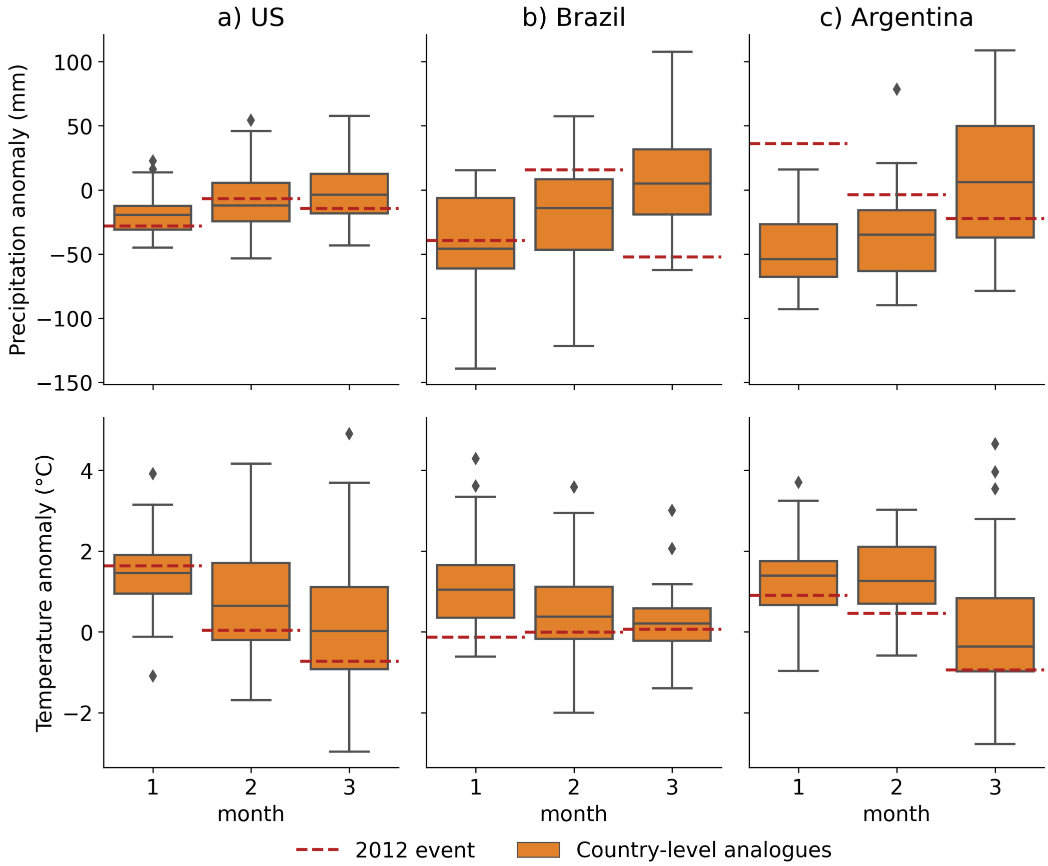

Figure 7. Same as Figure 4, but for country-level analogues (blue) across the three countries(orange) in the US (a), Brazil (b) and Argentina (c). 2012 event in red dashed line.

quency and damage is substantially lower. Thus, successful adaptation to changes in mean climate has the potential to minimise the majority of the climate change-caused impacts on simultaneous soybean failures across the Americas. This distinguishment between the climate change mechanisms that lead to changes in extreme events is highly relevant, as increased risk due to changes in mean climate and increased risk due to changes in climate variability asks for different adaptation responses (van der Wiel & Bintanja, 2021).

For the adaptation scenario, the 2012 analogues are primarily governed by compounding hot and dry conditions during the soybean reproductive season. Specifically, the analogues show on average higher mean temperatures than the original 2012 event in the second and third months, and lower precipitation values than the original event during the first two months of the season. On average, the analogues are expected to increase the productions losses in all three countries relative to the historical 2012 event.

Repeating the adaptation scenario analysis on a country level, we show a higher number of soybean failures in each of three countries (especially in the US) than in their aggregated form across the three countries. This implies that, despite a high number of country-level analogues in the future, the occurrence of joint crop yield failures in the three countries is not expected to significantly increase due to changes in climate variability alone. We do not investigate relations between simultaneous yield losses and large teleconnections, such as the El Niño–Southern Oscillation (ENSO). Previous studies show that La Niña phases are negatively correlated with soybean growing conditions in the

US and southeast South America, but positively correlated in the central Brazil region, potentially offsetting simultaneous soybean failures in the three countries (Anderson et al., 2018). This, and also our results show, that the joint analysis of crop yield anomalies in each of the important growing regions is necessary to robustly assess future risk of simultaneous soybean failures.

This study makes specific assumptions on concepts and boundary conditions. Many scenarios can be formulated accounting for the adaptation of crop management practices to mean climate trends, as is tacitly assumed in our "adaptation scenario". Actual adaptation encompass multiple measures, from changing the sowing dates (Fodor et al., 2017) and migrating the regions planted (Mourtzinis et al., 2019) to genetic modification of soybean cultivars (Snowdon et al., 2021), each having different consequences for soybean yields. Furthermore, we selected 3 GCMs with different climate sensitivities and considered the two most extreme SSP scenarios to obtain a diverse set of future scenarios. While these scenarios show clear signals in mean climate, there is sampling uncertainty in the occurrence and magnitude of extreme events. Sampling uncertainty can be addressed by using large ensembles, specifically designed to explore extremes in the data (Deser et al., 2020; van der Wiel et al., 2020). Finally, model or scenario uncertainty can be further explored by adopting a larger set of GCMs and SSPs.

We use soybean harvest areas documented for the year 2012 throughout all simulations, without regarding expansions of harvesting area. However, the expansion of soybeans is a significant matter, as deforestation in the Amazon has been associated with soybean expansion (Amaral et al., 2021; Song et al., 2021), and preserving natural vegetation helps protecting soybeans from weather extremes (Flach et al., 2021). We limit our analysis to soybean yields and production, but with the inclusion of socio-economic models, it is possible to extend the analysis to land use change (Zilli et al., 2020), poverty vulnerability (Byers et al., 2018), and impacts on global hunger through international trade (Janssens et al., 2020), among others.

5 Conclusion

In conclusion, we find that the increase of risk of simultaneous extreme soybean losses, such as the 2012 event, is primarily driven by the long term mean effects of climate change. Extreme soybean losses due to changes in climate variability are expected to increase regionally in all three countries, but a change in the joint occurrence of extreme soybean losses in the Americas due to climate variability is not evident from our simulations. Therefore, successful adaptation measures to mean climate change can help minimise the increase of risk of simultaneous extreme soybean losses in the Americas. The difference in impacts to changes in mean climate and changes in climate variability is large, and so are their potential adaptation options. Assessment of these climate impacts and adaptation responses requires dedicated analysis techniques. The use of historic events (such as the 2012 aggregated crop yield failure) provides a useful framework for these analyses.

6 Open Research

Code Availability Statement: The code for this experiment is available at: `https://github.com/dumontgoulart/soybean_failure_risk_cc_analogues`. The code will be deposited permanently at Zenodo if the article is eventually accepted.

Data Availability Statement: The observed soybean yield and harvested area data collected, combined and processed for this work and the future projections under different climate change levels are publicly available at `https://doi.org/10.7910/DVN/Q8D85C`, DOI:10.7910/DVN/Q8D85C (Goulart, 2022).

ISIMIP2a Simulation Data from Agricultural Sector, GFZ Data Services A. Arneth, J. Balkovic, P. Ciais, A. de Wit, D. Deryng, J. Elliott, C. Folberth, M. Glotter, T. Iizumi, R. C. Izaurralde, A. D. Jones, N. Khabarov, P. Lawrence, W. Liu, H. Mitter, C. Müller, S. Olin, T. A. M. Pugh, A. D. Reddy, G. Sakurai, E. Schmid, X. Wang, X. Wu, H. Yang, and M. Büchner, https://doi.org/10.5880/PIK.2017.006

Acknowledgments

This research has been supported by the European Union's Horizon 2020 research and innovation programme under grant agreement No 820712 (project RECEIPT, REmote Climate Effects and their Impact on European sustainability, Policy and Trade). The GSWP3-W5E5 climate dataset and growing season data were provided by the Global Gridded Crop Model Intercomparison (GGCMI) initiative and the Intersectoral Impact Model Intercomparison Project (ISIMIP). This work started at the Young Scientist Summer Program (YSSP) at the International Institute for Applied Systems Analysis (IIASA). We thank Raed Hamed, Timothy Tiggeloven, Jens de Bruijn, Aaron Alexander, Anaïs Couasnon, Sem Vijverberg and Rafaela Flach for the support throughout the work.

References

Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., ... Zheng, X. (2015). *TensorFlow: Large-scale machine learning on heterogeneous systems.* Retrieved from https://www.tensorflow.org/ (Software available from tensorflow.org)

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. *Heliyon*, *4*(11), e00938. Retrieved from https://www.sciencedirect.com/science/article/pii/S2405844018332067 doi: https://doi.org/10.1016/j.heliyon.2018.e00938

Amaral, D. F., de Souza Ferreira Filho, J. B., Chagas, A. L. S., & Adami, M. (2021). Expansion of soybean farming into deforested areas in the amazon biome: the role and impact of the soy moratorium. *Sustainability Science*, *16*(4), 1295–1312.

Anderson, W., Seager, R., Baethgen, W., & Cane, M. (2018). Trans-pacific enso teleconnections pose a correlated risk to agriculture. *Agricultural and Forest Meteorology*, *262*, 298-309. Retrieved from https://www.sciencedirect.com/science/article/pii/S0168192318302454 doi: https://doi.org/10.1016/j.agrformet.2018.07.023

Asseng, S., Ewert, F., Martre, P., Rötter, R. P., Lobell, D. B., Cammarano, D., ... others (2015). Rising temperatures reduce global wheat production. *Nature climate change*, *5*(2), 143–147.

Balkovič, J., van der Velde, M., Skalský, R., Xiong, W., Folberth, C., Khabarov, N., ... Obersteiner, M. (2014). Global wheat production potentials and management flexibility under the representative concentration pathways. *Global and Planetary Change*, *122*, 107–121. doi: 10.1016/j.gloplacha.2014.08.010

Banadkooki, F. B., Ehteram, M., Panahi, F., Sh. Sammen, S., Othman, F. B., & EL-Shafie, A. (2020). Estimation of total dissolved solids (tds) using new hybrid machine learning models. *Journal of Hydrology*, *587*, 124989. Retrieved from https://www.sciencedirect.com/science/article/pii/S0022169420304492 doi: https://doi.org/10.1016/j.jhydrol.2020.124989

Ben-Ari, T., Boé, J., Ciais, P., Lecerf, R., van der Velde, M., & Makowski, D. (2018). Causes and implications of the unforeseen 2016 extreme yield loss in the breadbasket of France. *Nature Communications*, *9*(1). Retrieved from http://dx.doi.org/10.1038/s41467-018-04087-x doi: 10.1038/s41467-018-04087-x

Breiman, L. (2001). Random Forests. , *2001*. Retrieved from https://doi.org/10.1023/A:1010933404324 doi: 10.1023/A:1010933404324

Butler, E. E., & Huybers, P. (2013). Adaptation of us maize to temperature variations. *Nature Climate Change*, *3*(1), 68–72.

Byers, E., Gidden, M., Leclère, D., Balkovic, J., Burek, P., Ebi, K., ... others (2018). Global exposure and vulnerability to multi-sector development and climate change hotspots. *Environmental Research Letters*, *13*(5), 055012.

Chollet, F., et al. (2015). *Keras.* https://keras.io.

Climpact. (2022). *Climpact.* Retrieved from https://github.com/ARCCSS-extremes/climpact/blob/master/www/user_guide/Climpact_user_guide.md

Crane-Droesch, A. (2018). Machine learning methods for crop yield prediction and climate change impact assessment in agriculture. *Environmental Research Letters*, *13*(11). doi: 10.1088/1748-9326/aae159

Daryanto, S., Wang, L., & Jacinthe, P.-A. (2017). Global synthesis of drought effects on cereal, legume, tuber and root crops production: A review. *Agricultural Water Management*, *179*, 18-33. Retrieved from https://www.sciencedirect.com/science/article/pii/S0378377416301470 (Special Issue on Improving Agricultural Water Productivity to Ensure Food Security under Changing Environments Overseen by: Brent Clothier) doi: https://doi.org/10.1016/j.agwat.2016.04.022

Deryng, D., Conway, D., Ramankutty, N., Price, J., & Warren, R. (2014). Global crop yield response to extreme heat stress under multiple climate change futures. *Environmental Research Letters*, *9*(3). doi: 10.1088/1748-9326/9/3/034011

Deser, C., Lehner, F., Rodgers, K. B., Ault, T., Delworth, T. L., DiNezio, P. N., ... others (2020). Insights from earth system model initial-condition large ensembles and future prospects. *Nature Climate Change*, *10*(4), 277–286.

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the coupled model intercomparison project phase 6 (cmip6) experimental design and organization. *Geoscientific Model Development*, *9*(5), 1937–1958. Retrieved from https://gmd.copernicus.org/articles/9/1937/2016/ doi: 10.5194/gmd-9-1937-2016

FAO. (2022). *Food and Agricultural Organization of the United Nations Statistical Database* (Tech. Rep.).

Feng, P., Wang, B., Liu, D. L., Waters, C., & Yu, Q. (2019). Incorporating machine learning with biophysical model can improve the evaluation of climate extremes impacts on wheat yield in south-eastern Australia. *Agricultural and Forest Meteorology*, *275*(November 2018), 100–113. Retrieved from https://doi.org/10.1016/j.agrformet.2019.05.018 doi: 10.1016/j.agrformet.2019.05.018

Flach, R., Abrahão, G., Bryant, B., Scarabello, M., Soterroni, A. C., Ramos, F. M., ... Cohn, A. S. (2021). Conserving the cerrado and amazon biomes of brazil protects the soy economy from damaging warming. *World Development*, *146*, 105582. Retrieved from https://www.sciencedirect.com/science/article/pii/S0305750X21001972 doi: https://doi.org/10.1016/j.worlddev.2021.105582

Fodor, N., Challinor, A., Droutsas, I., Ramirez-Villegas, J., Zabel, F., Koehler, A.-K., & Foyer, C. H. (2017, 09). Integrating Plant Science and Crop Modeling: Assessment of the Impact of Climate Change on Soybean and Maize Production. *Plant and Cell Physiology*, *58*(11), 1833-1847. Retrieved from https://doi.org/10.1093/pcp/pcx141 doi: 10.1093/pcp/pcx141

Folberth, C., Elliott, J., Müller, C., Balkovič, J., Chryssanthacopoulos, J., Izaurralde, R. C., ... others (2019). Parameterization-induced uncertainties and impacts of crop management harmonization in a global gridded crop model

ensemble. *PLoS One*, *14*(9), e0221862.
Folberth, C., Gaiser, T., Abbaspour, K. C., Schulin, R., & Yang, H. (2012). Regionalization of a large-scale crop growth model for sub-saharan africa: Model setup, evaluation, and estimation of maize yields. *Agriculture, ecosystems & environment*, *151*, 21–33.
Frieler, K., Schauberger, B., Arneth, A., Balkovič, J., Chryssanthacopoulos, J., Deryng, D., … Levermann, A. (2017). Understanding the weather signal in national crop-yield variability. *Earth's Future*, *5*(6), 605–616. doi: 10.1002/2016EF000525
Goulart, H. M. D. (2022). *Replication Data for: "Increase of simultaneous soybean failures due to climate change".* Harvard Dataverse. Retrieved from https://doi.org/10.7910/DVN/Q8D85C doi: 10.7910/DVN/Q8D85C
Goulart, H. M. D., van der Wiel, K., Folberth, C., Balkovic, J., & van den Hurk, B. (2021). Storylines of weather-induced crop failure events under climate change. *Earth System Dynamics*, *12*(4), 1503–1527. Retrieved from https://esd.copernicus.org/articles/12/1503/2021/ doi: 10.5194/esd-12-1503-2021
Hamed, R., van Loon, A. F., Aerts, J., & Coumou, D. (2021). Impacts of hot-dry compound extremes on us soybean yields. *Earth System Dynamics Discussions*, *2021*, 1–26. Retrieved from https://esd.copernicus.org/preprints/esd-2021-24/ doi: 10.5194/esd-2021-24
Hartman, G. L., West, E. D., & Herman, T. K. (2011). Crops that feed the World 2. Soybean-worldwide production, use, and constraints caused by pathogens and pests. *Food Security*, *3*(1), 5–17. doi: 10.1007/s12571-010-0108-x
Heinicke, S., Frieler, K., Jägermeyr, J., & Mengel, M. (2022, mar). Global gridded crop models underestimate yield responses to droughts and heatwaves. *Environmental Research Letters*, *17*(4), 044026. Retrieved from https://doi.org/10.1088/1748-9326/ac592e doi: 10.1088/1748-9326/ac592e
IBGE. (2022). *Levantamento sistemático da produção agrícola.* Brazilian Institute of Geography and Statistics. Retrieved from https://sidra.ibge.gov.br/tabela/6588
Iizumi, T., & Ramankutty, N. (2016). Changes in yield variability of major crops for 1981-2010 explained by climate change. *Environmental Research Letters*, *11*(3). doi: 10.1088/1748-9326/11/3/034003
IPCC. (2022). *Climate change 2022: Impacts, adaptation, and vulnerability. contribution of working group ii to the sixth assessment report of the intergovernmental panel on climate change* (H.-O. Pörtner et al., Eds.). Cambridge University Press. Retrieved from https://www.ipcc.ch/report/sixth-assessment-report-working-group-ii/
Jägermeyr, J., Müller, C., Ruane, A. C., Elliott, J., Balkovic, J., Castillo, O., … others (2021). Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. *Nature Food*, *2*(11), 873–885.
Janssens, C., Havlík, P., Krisztin, T., Baker, J., Frank, S., Hasegawa, T., … others (2020). Global hunger and climate change adaptation through international trade. *Nature Climate Change*, *10*(9), 829–835.
Jones, P. W. (1999). First-and second-order conservative remapping schemes for grids in spherical coordinates. *Monthly Weather Review*, *127*(9), 2204–2210.
Jägermeyr, J., Müller, C., Minoli, S., Ray, D., & Siebert, S. (2021). *Ggcmi phase 3 crop calendar.* Zenodo. Retrieved from https://doi.org/10.5281/zenodo.5062513 doi: 10.5281/zenodo.5062513
Kim, H. (2017). Global soil wetness project phase 3 atmospheric boundary conditions (experiment 1). *Data Integration and Analysis System (DIAS), Data set, https://doi. org/10.20783/DIAS*, *501*.
Lange, S. (2019). Trend-preserving bias adjustment and statistical downscaling with isimip3basd (v1.0). *Geoscientific Model Development*, *12*(7), 3055–3070. Re-

trieved from https://gmd.copernicus.org/articles/12/3055/2019/ doi: 10.5194/gmd-12-3055-2019

Lange, S., Menz, C., Gleixner, S., Cucchi, M., Weedon, G. P., Amici, A., ... others (2021). Wfde5 over land merged with era5 over the ocean (w5e5 v2. 0).

Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, *529*(7584), 84–87. doi: 10.1038/nature16467

Liu, B., Asseng, S., Müller, C., Ewert, F., Elliott, J., Lobell, D. B., ... others (2016). Similar estimates of temperature impacts on global wheat yield by three independent methods. *Nature Climate Change*, *6*(12), 1130–1136.

Lobell, D. B., & Burke, M. B. (2010). On the use of statistical models to predict crop yield responses to climate change. *Agricultural and forest meteorology*, *150*(11), 1443–1452.

Lobell, D. B., & Field, C. B. (2007). Global scale climate-crop yield relationships and the impacts of recent warming. *Environmental Research Letters*, *2*(1). doi: 10.1088/1748-9326/2/1/014002

Lobell, D. B., & Tebaldi, C. (2014). Getting caught with our plants down: The risks of a global crop yield slowdown from climate trends in the next two decades. *Environmental Research Letters*, *9*(7). doi: 10.1088/1748-9326/9/7/074003

MAGYP. (2022). *Datos agricultura, ganadería y pesca.* The Ministry of Agriculture, Livestock and Fisheries. Retrieved from https://datos.magyp.gob.ar/dataset

Meehl, G. A., Senior, C. A., Eyring, V., Flato, G., Lamarque, J.-F., Stouffer, R. J., ... Schlund, M. (2020). Context for interpreting equilibrium climate sensitivity and transient climate response from the cmip6 earth system models. *Science Advances*, *6*(26), eaba1981. Retrieved from https://www.science.org/doi/abs/10.1126/sciadv.aba1981 doi: 10.1126/sciadv.aba1981

Moore, F. C., & Lobell, D. B. (2015). The fingerprint of climate trends on european crop yields. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(9), 2970–2975. doi: 10.1073/pnas.1409606112

Mourtzinis, S., Specht, J. E., & Conley, S. P. (2019). Defining optimal soybean sowing dates across the us. *Scientific Reports*, *9*(1), 1–7.

Panahi, F., Ehteram, M., Ahmed, A. N., Huang, Y. F., Mosavi, A., & El-Shafie, A. (2021). Streamflow prediction with large climate indices using several hybrid multilayer perceptrons and copula bayesian model averaging. *Ecological Indicators*, *133*, 108285. Retrieved from https://www.sciencedirect.com/science/article/pii/S1470160X2100950X doi: https://doi.org/10.1016/j.ecolind.2021.108285

Ray, D. K., Gerber, J. S., Macdonald, G. K., & West, P. C. (2015). Climate variation explains a third of global crop yield variability. *Nature Communications*, *6*, 1–9. doi: 10.1038/ncomms6989

Ray, D. K., West, P. C., Clark, M., Gerber, J. S., Prishchepov, A. V., & Chatterjee, S. (2019). Climate change has likely already affected global food production. *PLoS ONE*, *14*(5), 1–18. doi: 10.1371/journal.pone.0217148

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Arneth, A., ... Jones, J. W. (2014). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3268–3273. doi: 10.1073/pnas.1222463110

Rosenzweig, C., Ruane, A. C., Antle, J., Elliott, J., Ashfaq, M., Chatta, A. A., ... others (2018). Coordinating agmip data and models across global and regional scales for 1.5 c and 2.0 c assessments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *376*(2119), 20160455.

Schauberger, B., Archontoulis, S., Arneth, A., Balkovic, J., Ciais, P., Deryng, D.,

… Frieler, K. (2017). Consistent negative response of US crops to high temperatures in observations and crop models. *Nature Communications*, *8*. doi: 10.1038/ncomms13931

Schewe, J., Gosling, S. N., Reyer, C., Zhao, F., Ciais, P., Elliott, J., … Warszawski, L. (2019). State-of-the-art global models underestimate impacts from climate extremes. *Nature Communications*, *10*(1), 1–14. doi: 10.1038/s41467-019-08745-6

Shahhosseini, M., Hu, G., Huber, I., & Archontoulis, S. V. (2021). Coupling machine learning and crop modeling improves crop yield prediction in the us corn belt. *Scientific reports*, *11*(1), 1–15.

Snowdon, R. J., Wittkop, B., Chen, T.-W., & Stahl, A. (2021). Crop adaptation to climate change as a consequence of long-term breeding. *Theoretical and Applied Genetics*, *134*(6), 1613–1623.

Song, X.-P., Hansen, M. C., Potapov, P., Adusei, B., Pickering, J., Adami, M., … others (2021). Massive soybean expansion in south america since 2000 and implications for conservation. *Nature sustainability*, *4*(9), 784–792.

Stevenson, S., Coats, S., Touma, D., Cole, J., Lehner, F., Fasullo, J., & Otto-Bliesner, B. (2022). Twenty-first century hydroclimate: A continually changing baseline, with more frequent extremes. *Proceedings of the National Academy of Sciences*, *119*(12), e2108124119. Retrieved from `https://www.pnas.org/doi/abs/10.1073/pnas.2108124119` doi: 10.1073/pnas.2108124119

USDA. (2022). *National agricultural statistics service.* National Agricultural Statistics Service. Retrieved from `https://data.nal.usda.gov/dataset/nass-quick-stats`

van der Wiel, K., Selten, F. M., Bintanja, R., Blackport, R., & Screen, J. A. (2020). Ensemble climate-impact modelling: extreme impacts from moderate meteorological conditions. *Environmental Research Letters*, *15*(3). doi: 10.1088/1748-9326/ab7668

van der Wiel, K., & Bintanja, R. (2021). Contribution of climatic changes in mean and variability to monthly temperature and precipitation extremes. *Communications Earth & Environment*, *2*(1), 1–11.

Vogel, E., Donat, M. G., Alexander, L. V., Meinshausen, M., Ray, D. K., Karoly, D., … Frieler, K. (2019). The effects of climate extremes on global agricultural yields. *Environmental Research Letters*, *14*(5). doi: 10.1088/1748-9326/ab154b

Vogel, J., Rivoire, P., Deidda, C., Rahimi, L., Sauter, C. A., Tschumi, E., … Zscheischler, J. (2021). Identifying meteorological drivers of extreme impacts: an application to simulated crop yields. *Earth System Dynamics*, *12*(1), 151–172. Retrieved from `https://esd.copernicus.org/articles/12/151/2021/` doi: 10.5194/esd-12-151-2021

Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O., & Schewe, J. (2014). The inter-sectoral impact model intercomparison project (ISI-MIP): Project framework. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3228–3232. doi: 10.1073/pnas.1312330110

Williams, J. R., et al. (1995). The epic model. *Computer models of watershed hydrology.*, 909–1000.

Wing, I. S., De Cian, E., & Mistry, M. N. (2021). Global vulnerability of crop yields to climate change. *Journal of Environmental Economics and Management*, *109*, 102462. Retrieved from `https://www.sciencedirect.com/science/article/pii/S0095069621000450` doi: https://doi.org/10.1016/j.jeem.2021.102462

Wolski, P., Lobell, D., Stone, D., Pinto, I., Crespo, O., & Johnston, P. (2020). On the role of anthropogenic climate change in the emerging food crisis in southern Africa in the 2019–2020 growing season. *Global Change Biology*, *2020*(February), 1–2. doi: 10.1111/gcb.15047

Xie, W., Xiong, W., Pan, J., Ali, T., Cui, Q., Guan, D., … Davis, S. J. (2018). Decreases in global beer supply due to extreme drought and heat. *Nature Plants*, *4*(11), 964–973. Retrieved from http://dx.doi.org/10.1038/s41477-018-0263-1 doi: 10.1038/s41477-018-0263-1

Xu, J., Gao, J., de Holanda, H. V., Rodríguez, L. F., Caixeta-Filho, J. V., Zhong, R., … others (2021). Double cropping and cropland expansion boost grain production in brazil. *Nature Food*, *2*(4), 264–273.

Yu, Q., You, L., Wood-Sichra, U., Ru, Y., Joglekar, A. K. B., Fritz, S., … Yang, P. (2020). A cultivated planet in 2010 – part 2: The global gridded agricultural-production maps. *Earth System Science Data*, *12*(4), 3545–3572. Retrieved from https://essd.copernicus.org/articles/12/3545/2020/ doi: 10.5194/essd-12-3545-2020

Zampieri, M., Ceglar, A., Dentener, F., & Toreti, A. (2017, jun). Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. *Environmental Research Letters*, *12*(6), 064008. Retrieved from https://iopscience.iop.org/article/10.1088/1748-9326/aa723b doi: 10.1088/1748-9326/aa723b

Zhang, D., Zang, G., Li, J., Ma, K., & Liu, H. (2018). Prediction of soybean price in China using QR-RBF neural network model. *Computers and Electronics in Agriculture*, *154*(June), 10–17. Retrieved from https://doi.org/10.1016/j.compag.2018.08.016 doi: 10.1016/j.compag.2018.08.016

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., … Asseng, S. (2017, aug). Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of Sciences*, *114*(35), 9326–9331. Retrieved from http://www.pnas.org/lookup/doi/10.1073/pnas.1701762114 doi: 10.1073/pnas.1701762114

Zhu, X., & Troy, T. J. (2018). Agriculturally Relevant Climate Extremes and Their Trends in the World's Major Growing Regions. *Earth's Future*, *6*(4), 656–672. doi: 10.1002/2017EF000687

Zilli, M., Scarabello, M., Soterroni, A. C., Valin, H., Mosnier, A., Leclère, D., … Ramos, F. M. (2020). The impact of climate change on brazil's agriculture. *Science of The Total Environment*, *740*, 139384. Retrieved from https://www.sciencedirect.com/science/article/pii/S0048969720329016 doi: https://doi.org/10.1016/j.scitotenv.2020.139384

Zscheischler, J., Orth, R., & Seneviratne, S. (2017). Bivariate return periods of temperature and precipitation explain a large fraction of European crop yields. *Biogeosciences Discussions*(February), 1–18. doi: 10.5194/bg-2017-21