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Increase of Simultaneous Soybean Failures Due To Climate Change

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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

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract While soybeans are among the most consumed crops in the world, most of its production lies in the US, Brazil, and Argentina. The concentration of soybean growing regions in the Americas renders the supply chain vulnerable to regional disruptions. In 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. 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 long-term trends in mean climate increase the frequency of 2012 analogs by 11–16 times and the magnitude by 4–15% compared to changes in climate variability only depending on the global climate scenario. 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 analyze 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 globalized agricultural system might face in the future.

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Adverse weather conditions are common causes of crop failures. Previous studies show crop yield variability is affected by interannual weather variability (Frieler et al., 2017; Lobell & Field, 2007; Ray et al., 2015). Specifically, climate extremes (Lesk et al., 2016; Vogel et al., 2019; Zampieri et al., 2017) and multivariate or temporally compounding events (Ben-Ari et al., 2018; Hamed et al., 2021; van der Wiel et al., 2020; Vogel et al., 2021; Zscheischler et al., 2017) 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; Iizumi & Ramankutty, 2016; Moore & Lobell, 2015; Ray et al., 2019; Wolski et al., 2020; Zhao et al., 2017; Zhu & Troy, 2018).

The agricultural sector is expected to be further affected by continued climate change in the future (Lobell & Tebaldi, 2014; Rosenzweig et al., 2018; Schauberger et al., 2017; 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; Stevenson et al., 2022; Vogel et al., 2019), 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 is Global Gridded Crop Models (GGCMs, see Section 2). GGCMs are global implementations of crop models, 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 utilize 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 (Heinicke et al., 2022; Schewe et al., 2019). 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 expand on process-based crop models by including (extreme) climate indices that the crop model might not be able to process. Conversely, hybrid models include biophysical processes from the process-based crop model that might not be easily available for a statistical model to be trained on, such as biological, physical, and chemical processes (Feng et al., 2019, 2020). 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 analogs (Goulart et al., 2021; van der Wiel et al., 2020) 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 analogs. We analyze 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 analyze potential changes in analog 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, representing both synchronized and localized crop yield decline. We determine whether the risk of extreme soybean failures across the Americas is changing due to climate change, disentangling changes in mean climate change from 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 limited our analysis to areas with rainfed soybeans to better capture the interactions between climate and crops. We used the SPAM2010 data set (Yu et al., 2020), which estimates harvest areas for irrigated and rainfed soybeans around the year 2010, to select the rainfed harvest areas (more information in section S1 in Supporting Information S1). We resampled the data set a 0.5° × 0.5° grid to match the other data sets using the first order conservative remapping scheme (Jones, 1999).

2.2. Climate and Crop Data

To build the hybrid model, we used simulated climate data, simulated yields, and observed yields. Historical and bias-corrected projected climate data were obtained from the Intersectoral Impact Model Intercomparison Project (Warszawski et al., 2014). The climate data have daily values at 0.5° × 0.5° spatial resolution and are divided in two simulation periods: historical and future projections. The historical run (1901–2015) consists of the GSWP3-W5E5 data set, a combination of two global data sets 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 using GSWP3-W5E5 as described in Lange (2019). Among the five GCMs available in ISIMIP, we selected these GCMs as they have different climate sensitivities to CO_2 concentration increases: low, mid and high sensitivities respectively (Table S1 in Supporting Information S1, Jägermeyr, Müller, Minoli, et al., 2021; Jägermeyr, Müller, Ruane, et al., 2021; Meehl et al., 2020). The future projections are forced by two Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathway (RCP) combinations: SSP1-2.6 (low-emission future) and SSP5-8.5 (high-emission future). We selected these two scenarios as they represent the lower and upper boundaries of the available future scenarios in terms of future global emission pathways, respectively. The combination of GCMs and SSPs allow for the estimation of climate risk under six different future scenarios (Jägermeyr, Müller, Minoli, et al., 2021; Jägermeyr, Müller, Ruane, et al., 2021). More information on the GCMs and SSPs can be found in the documentation underlying the Coupled Model Intercomparison 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 is a global implementation of the Environmental Policy Integrated Climate (EPIC) field-scale crop model (Williams, 1995) within a geospatial framework that provides input data (climate, soil, crop management) for each simulation unit (i.e., pixel). The EPIC model is run for each simulation unit treating it as a representative field. EPIC-IIASA covers the entire global land surface at a spatial resolution of 0.5° × 0.5°. All crop model simulations considered CO_2 fertilization effect on crop growth. Within EPIC, atmospheric CO_2 concentration modulates radiation use efficiency, the model's representation of photosynthesis and biomass accumulation, and potential evapotranspiration. For the latter, the Penman-Monteith approach was used as documented in Stockle et al. (1992), which accounts for CO_2 effects on leaf resistance and results in lower transpirative water demand at higher CO_2 concentrations.

Observed yields from census data were used to train the hybrid model. We obtained observed data for yields and harvest areas for soybeans at a county level directly from the national authorities of each country analyzed 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 cleansing (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 observed yield and harvest areas data sets for the three countries were resampled from the county level to a 0.5° × 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. We selected observed data from 1979 to 2015 based on data availability for the three countries (later also used to train and validate the hybrid model). For the cases of Argentina and Brazil, where cropping seasons includes more than one calendar year, we consider the harvest year as reference. 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 using the R package Climpact (Climpact (2022) to generate 17 multiple climatic indices divided in temperature and precipitation types (list of generated climatic indices available in Table S2 in Supporting Information S1). The yield data (both simulated and observed) 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 timeseries for both historical data and projections, and selected the method with least squared errors.

Given the seasonal differences between the regions analyzed, 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 3-month season starting 1 month before the month in which soybeans reach the maturity date and ending 1 month after that month. The soybean maturity date was obtained from the GGCMI Phase 3 crop calendar (Jägermeyr, Müller, Minoli, et al., 2021; Jägermeyr, Müller, Ruane, 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 3-month season simulated by a Random Forest model (Breiman, 2001).

2.4. Hybrid Model Development

The hybrid model is built by combining the simulated soybean yields from EPIC-IIASA and the climate indices obtained in the previous step as predictors for a statistical model calibrated to observed soybean yields. We also added for each grid cell the country label to represent the influence of nonclimatic 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, 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 Table S3 in Supporting Information S1).

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, details in Section S2 in Supporting Information S1), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Then we calculated the sum of errors of each model for the 2012 years to determine which model represents extreme conditions best.

2.5. Investigating the Risk of Future Failures

We adopted the concept of impact analogs to assess the future risk of soybean failures. Impact analogs have been shown to better represent the risk estimation of extreme impact events than weather analogs (Goulart et al., 2021, van der Wiel et al., 2020). Impact analogs (hereafter shortened to "analogs") 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 analogs. We also investigated the associated climatic conditions, and the spatial distributions of the analogs to determine how each country contributed to the total yield loss. In addition, we analyzed country scale analogs 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

Table 1
Out of Sample Performance of the Models for Three Metrics: Coefficient of Determination (R^2, No Unit), Mean Absolute Error (MAE, (ton/ha)^2), and Root Mean Squared Error (RMSE, ton/ha)

Model	R^2	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

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: (a) 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"; (b) 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 (Table S4 in Supporting Information S1) 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 analyzed together (Table 1) and individually (Table S5 in Supporting Information S1). 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 (Figure 1a and Figure S1 in Supporting Information 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

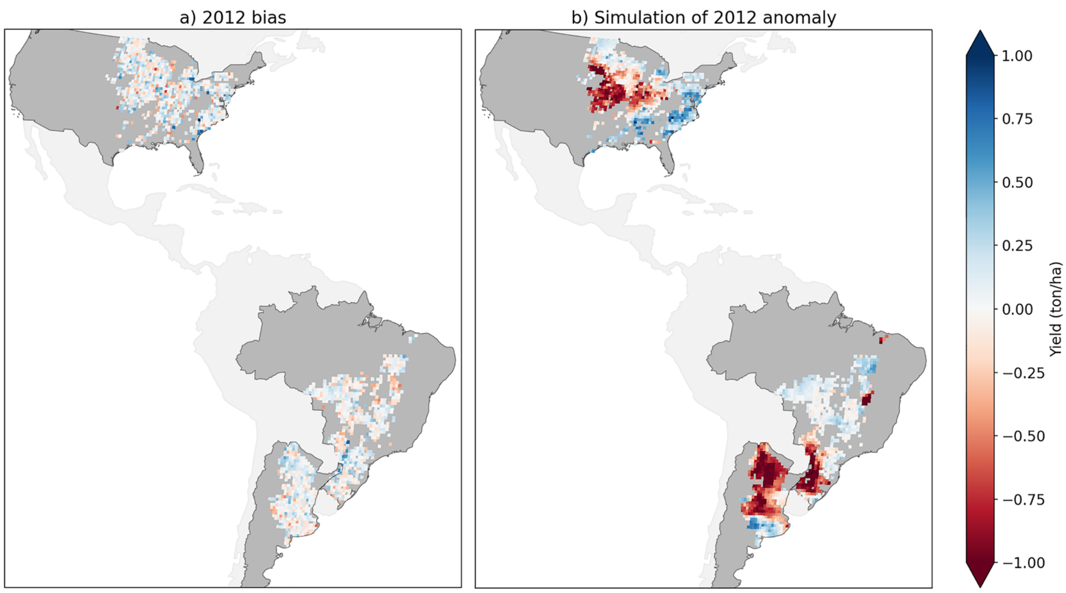

Figure 1. (a) Crop yield difference between the hybrid model simulation and the observed data for the 2012 event. (b) Simulated yield anomalies by the hybrid model for the year 2012 with respect to the climatology. Results shown in ton/ha.

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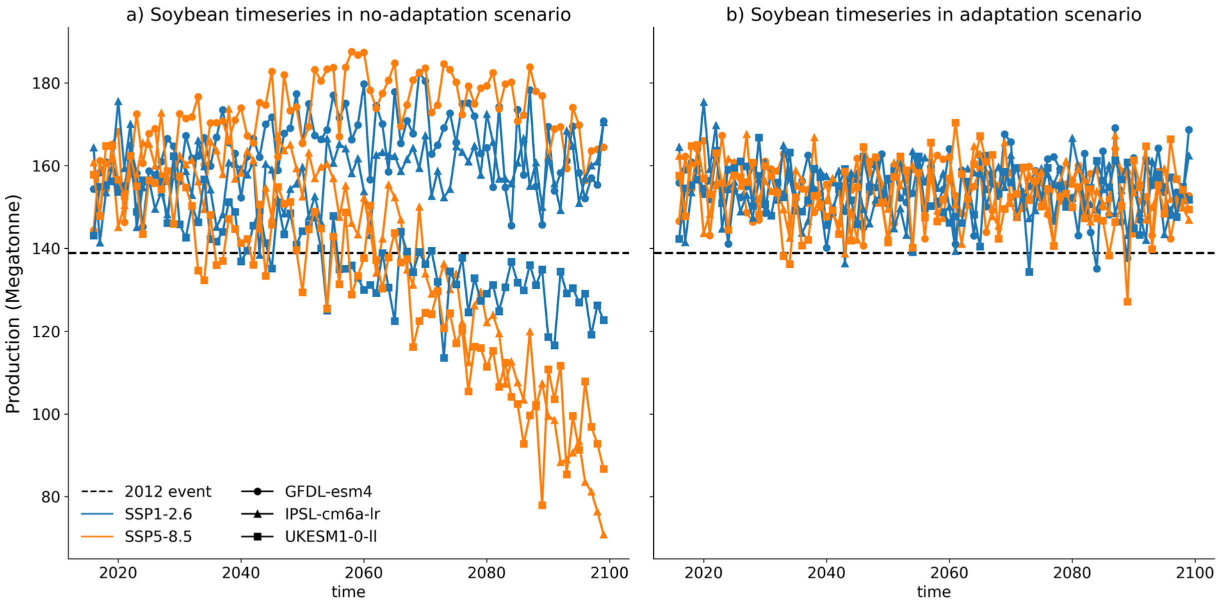

Figure 2. (a) Projected soybean yields for the no adaptation scenario. (b) Same but for the adaptation scenario. Shared Socioeconomic Pathways (SSPs) are defined by color (blue SSP1-2.6 and orange SSP5-8.5) and Global Gridded Crop Models (GGCMs) by symbols (circle: GFDL-esm4, triangle: IPSL-cm6a, square: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

information on SI section S3, 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. As a consequence, the results in the following sections are based only on the hybrid model outputs. For the year 2012, the hybrid model shows an accumulated loss (negative anomaly) of 21.1 Mt with respect to the climatology (2000–2015). This is due to losses of 7.2 Mt in the US, 4.9 Mt in Brazil and 9 Mt in Argentina (Figure 1b).

3.2. Number of Future Impact Analog Events

We investigate the total number of analog events of the 2012 event for both adaptation and no adaptation scenarios. In the no adaptation scenario, the occurrence of analogs is heavily dependent on the future climatic forcing conditions. For SSP5-8.5, a high occurrence of 2012 analogs (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 Figure S2a in Supporting Information S1). For SSP1-2.6, fewer analogs are observed (43), and only one member shows mean climatological values crossing the 2012 threshold. The magnitude of the analogs 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 S2c in Supporting Information S1). The simulations show that the soybean projections vary across the GCM ensemble members, partly due to differences in climate sensitivity to increasing CO_2 concentrations: the future scenario not crossing the 2012 threshold in SSP5-8.5 is based on the GCM with lowest climate sensitivity to CO_2 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 CO_2 concentration levels (ECS: 5.3°C, for more information see Table S1 in Supporting Information S1 and Jägermeyr, Müller, Minoli, et al., 2021; Jägermeyr, Müller, Ruane, et al., 2021; Meehl et al., 2020).

The adaptation scenario shows a low number of 2012 analogs (Figure 2b). Nine analogs are obtained in the future scenarios tested, four for the SSP1-2.6 and five for the SSP5-8.5 (Figure S2b in Supporting Information S1). 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 S2d in Supporting Information S1). Therefore, 2012 analogs are approximately 11 and 16 times more likely to occur in the no adaptation scenario than in the adaptation scenario for the SSP1-2.6 and SSP5-8.5, respectively. The average magnitude of the analogs is also 4% and 15% higher in the no adaptation scenario than in the adaptation for SSP1-2.6 and SSP5-8.5, respectively. The results suggest that trends in mean climate dominate the risk of 2012 analogs to occur.

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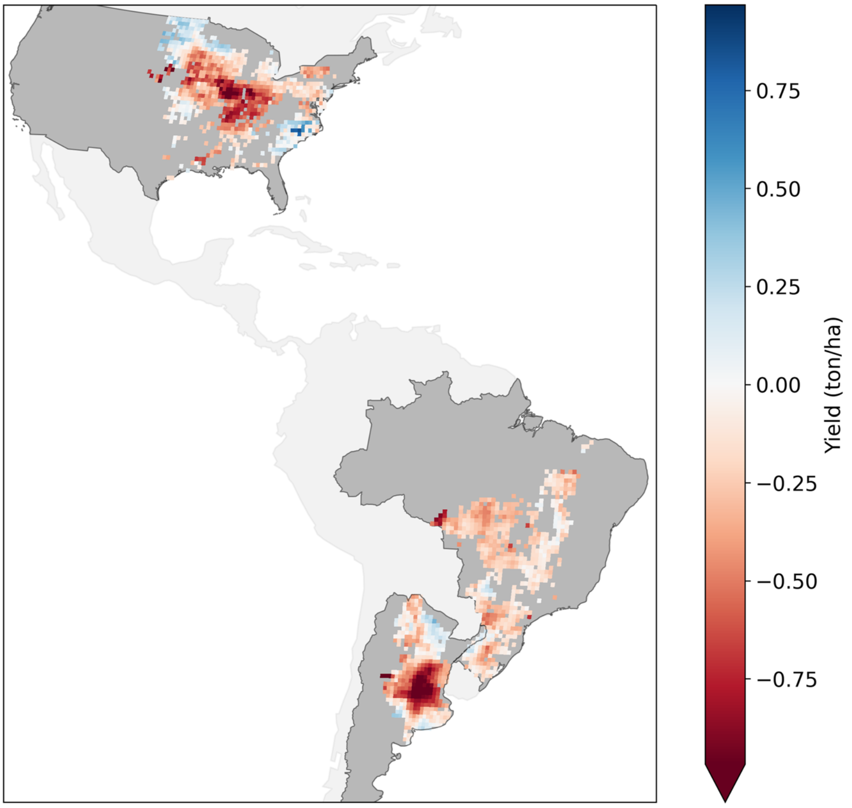

Figure 3. Spatial distribution of soybean yield anomalies in the adaptation scenario averaged across all 2012 analogs compared to the 2012 event. Units are in ton/ha.

3.3. Impact Analogs in Adaptation Scenario

We run a spatial analysis of the nine impact analogs 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 analog years (Figure 3). When compared to the 2012 event, analogs losses in the US, Brazil and Argentina increase on average (in brackets the 95% confidence interval) by −1.5 Mt (−4.1 Mt, 1.0 Mt), −0.5 Mt (−5.9 Mt, 4.8 Mt), −0.6 Mt (−4.0 Mt, 2.8 Mt), respectively. Thus, the expected damages associated with 2012 analogs are shown to increase in the three countries when compared to the 2012 event.

We assess the climatic conditions of the impact analogs for the adaptation scenario to check for possible changes in the driving climatic anomalies (Figure 4). The average climatic conditions of the analogs are drier than the 2012 event during the first and second months of the season, but wetter in the last month of the season. The analogs 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 analogs 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 S3 in Supporting Information S1). While the analogs 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 analogs (Goulart et al., 2021, van der Wiel et al., 2020).

3.4. Country-Level Analogs

While the simultaneous soybeans failures are the most impactful events for the globalized markets, we also explore the risks associated with soybean failures in each country for the adaptation scenario. We refer to these as "country-level analogs," and they comprise a different selection of years to the aggregated 2012 analogs. The number of country-level analogs of the 2012 event is 3.4, 4.4, and 9.3 times higher for Argentina (31), Brazil (40),

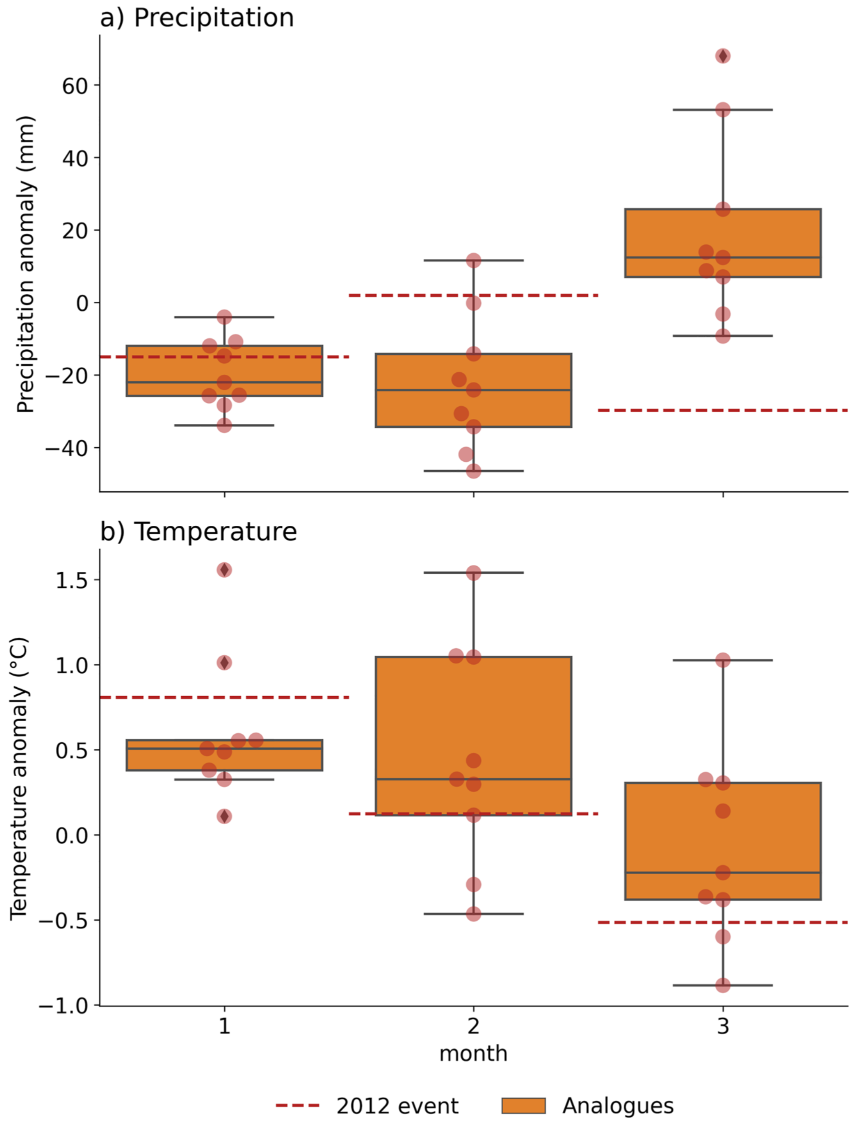

Figure 4. Climatic conditions for the 2012 analogs (in orange) compared with the simulated 2012 event (red dashed lines). Red dots represent individual analog events. The whiskers denote the distance between the upper and lower quartiles, and the values outside are the outliers (diamonds). Precipitation and average daily maximum temperature values are represented by "prcptot_x" (mm/month) and "txm_x" (°C), respectively, with x representing the relative month of the season.

and the US (84), respectively, than for the aggregated 2012 analogs across the three countries (Figure 5a). The average losses associated with country-level analogs increase by −2.7 Mt (−3.1 Mt, −2.2 Mt) in the US, −2.5 Mt (−3.7 Mt, −1.4 Mt) in Brazil, and −2.4 Mt (−3.2 Mt, −1.6 Mt) in Argentina with respect to the corresponding country-level losses observed in 2012 (Figure 5b). Therefore, country-level analogs are more frequent than aggregated analogs in the future, and the average losses of country-level analogs increase with respect to the historical 2012 event for all three countries individually. In addition, the US shows the highest number of country-level analogs, significantly higher than the other two countries.

We compare the occurrence of country-level analogs in one or more countries with the occurrence of 2012 analogs (aggregated across all countries) to identify cooccurrences 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 analogs coinciding with country-level analogs in all three countries. Instead, 2012 analogs occur due to one or two countries presenting country-level analogs in the same year, but no single country dominates the frequency of 2012 analogs. Our findings highlight the complexity of simultaneous soybean losses across the

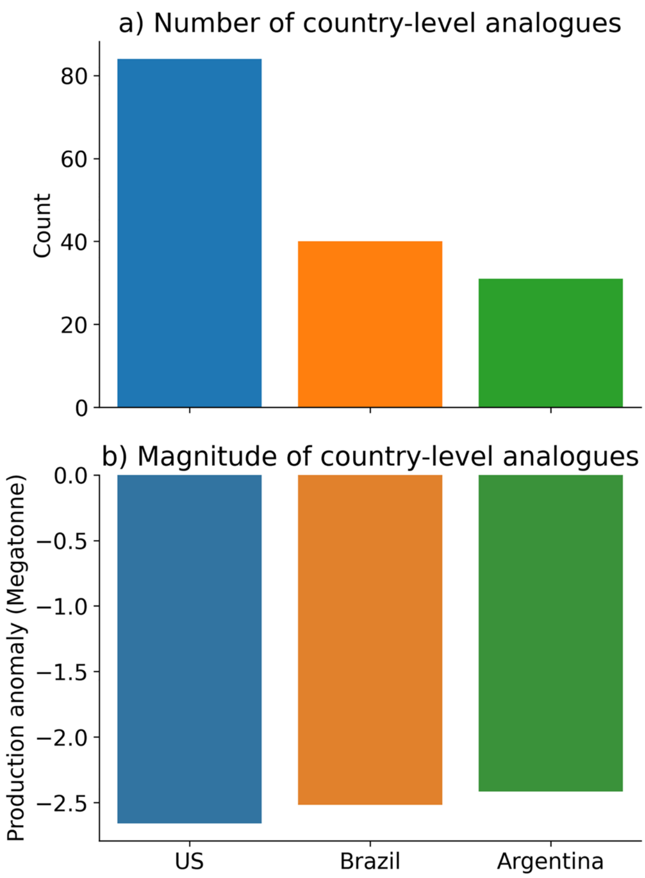

Figure 5. (a) Barplots showing the number of country-level analogs per country. (b) Barplots showing the average conditions of country-level analogs of the 2012 event for each country. Black vertical lines indicate 95% spread within events.

regions studied, and show that all three countries should be taken into consideration when exploring the global risk of extreme soybean failures.

For each country, we explore the regional climatic conditions linked with the country-level analogs and compare them to the 2012 climatic conditions (Figure 7). The country-level analogs 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 3 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 3 months, while precipitations levels are drier for the first and second months. Relative to the historical climatology, the country-level analogs for all countries are the result of hot and dry climatic conditions (Figure S4 in Supporting Information S1).

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, Müller, Minoli, et al., 2021; Jägermeyr, Müller, Ruane, 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). Analogs of the simultaneous production failures in these countries as experienced in 2012 were explored under future climate conditions. We used climate model simulations driven 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 (Goulart et al., 2021, van der Wiel et al., 2020), 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; Jägermeyr, Müller, Minoli, et al., 2021; Jägermeyr, Müller, Ruane, et al., 2021; Schauberger et al., 2017; Wing 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 risk of 2012 analogs is substantially lower: roughly 11 and 16 times less frequent and on average 4% and 15% less intense for SSP1-2.6 and SSP5-8.5, respectively. Thus, successful adaptation to changes in mean climate has the potential to minimize 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 analogs are primarily governed by compounding hot and dry conditions during the soybean reproductive season. Specifically, the analogs 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 2 months of the season. On average, the analogs 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 analogs in the future, the occurrence of joint crop yield

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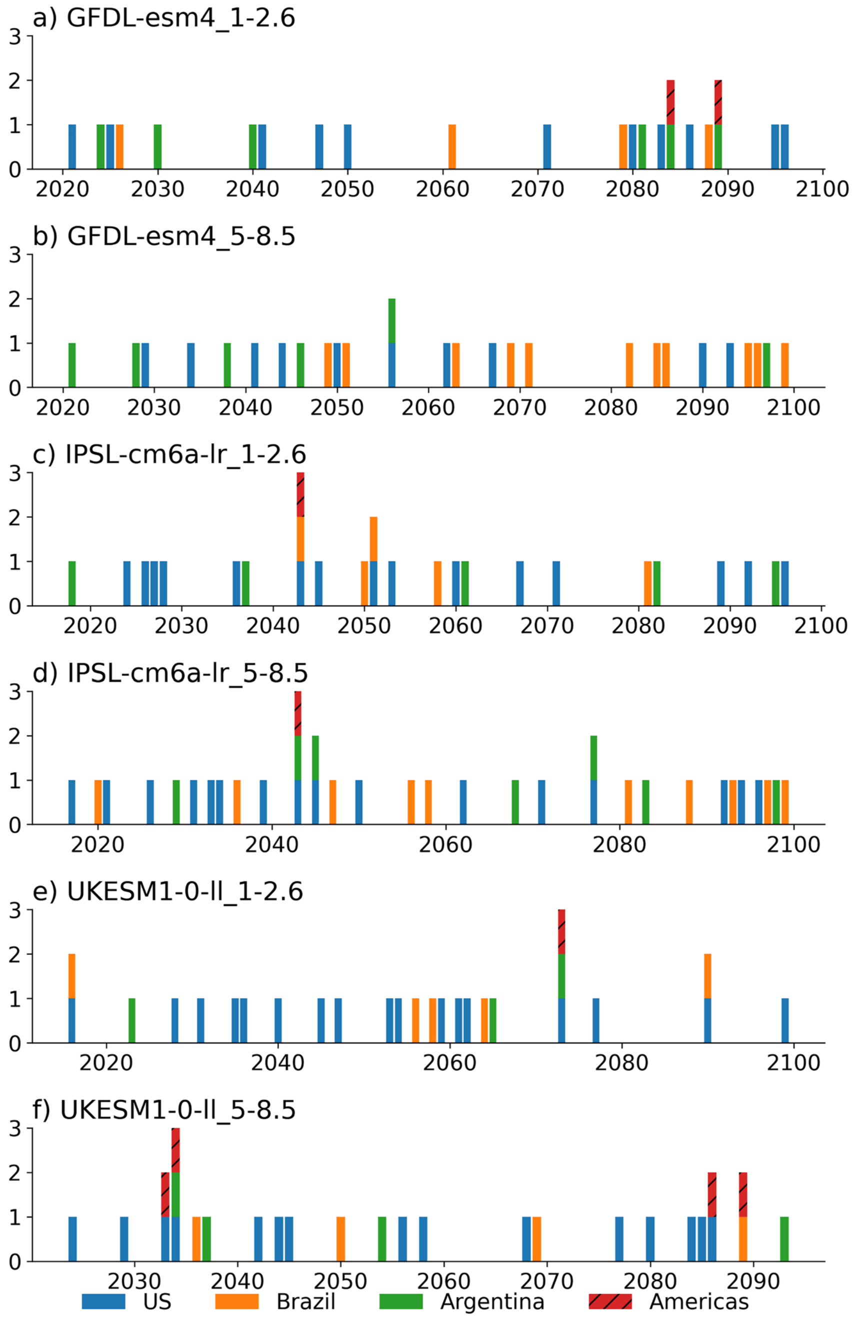

Figure 6. Occurrences of local analogs and simultaneous analogs to the historical event of 2012. Each panel is a combination of Global Gridded Crop Models (GGCMs) (GFDL-esm4, IPSL-cm6a-lr, UKESM1-0-ll) and SSPs (1–2.6, 5–8.5).

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

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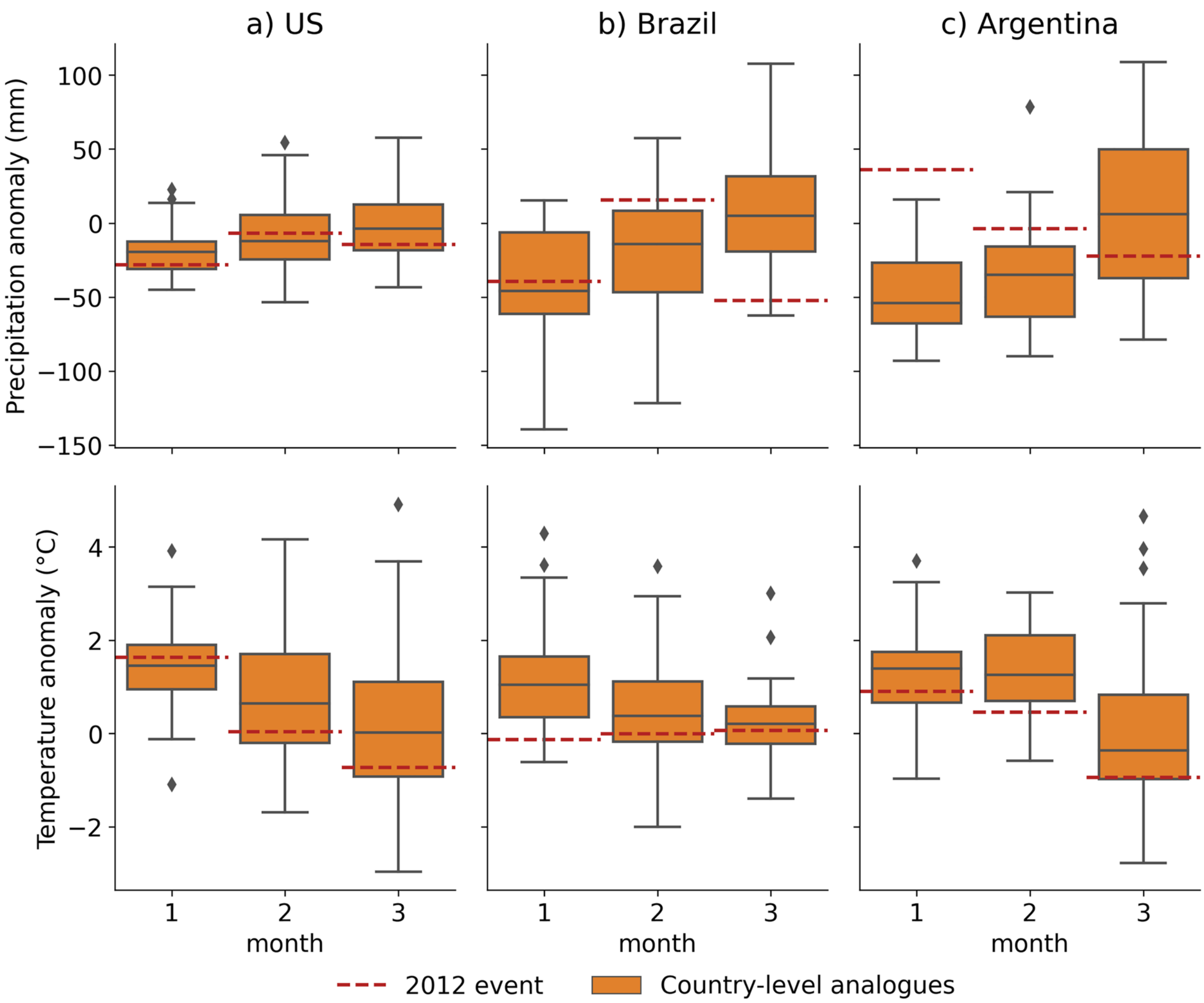

Figure 7. Same as Figure 4, but for country-level analogs (blue) across the three countries(orange) in the US (a), Brazil (b), and Argentina (c). 2012 event in red dashed line.

"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. As a consequence of the removal of long-term trends in the adaptation scenario, the effects of CO_2 fertilization are also not considered, only for the no adaptation scenario. Furthermore, we selected three 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 focus on rainfed harvest areas based on data from 2010. Expansion of irrigation areas in subsequent years could lead to changes in the sensitivity of the studied area to weather variability. We limit our analysis to soybean yields and production, but with the inclusion of socioeconomic 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 minimize 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.

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, https://doi.org/10.7910/DVN/Q8D85C (Goulart, 2022). ISIMIP2a Simulation Data from Agricultural Sector, GFZ Data Services (Arneth et al., 2017, https://doi.org/10.5880/PIK.2017.006). The code used for this experiment is available at: https://doi.org/10.5281/zenodo.7746911 (Goulart, 2023).

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