Potential impacts of concurrent and recurrent climate extremes on the global food system by 2030

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Abstract
The risk of food-supply instability is expected to increase along with the frequency and intensity of extreme agro-climatic events in many regions. Assessing the sensitivity of the global agricultural system to evolving extremes requires the probability of occurrence of such events to be estimated and their links with potential food supply and demand culminations to be established. From this perspective, in this article we implement a novel approach that can be used as a tool to inform decision-makers about the resilience of agricultural markets to climate extremes. By incorporating simulated climate-stress events into a partial-equilibrium model of interconnected agricultural commodity markets, we examine the complex manifestations of grain supply, demand and prices attributable to hazardous extremes. Market outcomes are further synthesized into coherently defined vulnerability and risk indicators. The proposed framework currently covers compound heat and water anomalies at the country level, potentially concurrent and recurrent, that impact annual crop yields and market balances in a recursive-dynamic manner until 2030. Our findings indicate that extreme-climate anomalies significantly distort expected market equilibria in the medium term. Moreover, extreme global prices may result either from climate anomalies in single key countries or from simultaneous events in many regions. Last but not least, trade and storage come forth as important alleviative mechanisms of the market uncertainty provoked by recurrent extremes.

1. Introduction

Recent insurance statistics suggest an exponential increase in the frequency of natural hazards by 2.6% per year in the last four decades (Munich Re, NatCatSERVICE 2018). A closer examination by hazard type revealed that climatological and hydrological ones together have grown twice as fast as earthquakes, volcanic eruptions and storms (appendix A.1 available online at stacks.iop.org/ERL/16/124021/mmedia). Furthermore, low-probability high-impact events appear to be driving economic losses, as 72% of the global damage attributable to temperature and water-related anomalies since 1980 emanated from only 6% of (‘catastrophic’) events. Against this background, and considering that the last four decades have been successively warmer than any preceding decade since 1850 (WMO 2020), the assertion made in the Fifth Assessment Report of the IPCC that ‘extreme climate events are on the rise’ keeps gaining momentum.

Crop production is inherently vulnerable to biophysical stress. Climatic factors that distort fundamental physiological processes during critical phenological stages lead to organ fragility, grain deformation and parthenocarpy, ultimately resulting in lower crop yield (Porter and Gawith 1999, Das 2005, Luo 2011, Anderson et al 2019, Chen et
2019, Li et al. 2019). A well-documented example of such direct impacts is maize, in which case heat stress reduces pollen germination and photosynthetic efficiency and water deficit leads to anoxia and higher incidence of root diseases, while compound stress in the reproductive stage aggravates the yield loss that would otherwise occur from individual stressors. Progressively and after an extreme agroclimatic event indirect impacts may also have to be incurred. Those range from site-level biotic stress, such as harmful pests and diseases, to large-scale socioeconomic repercussions upon food and feed prices, the value of production, food-trade patterns and balances, and even food security. Recent prominent examples of low-probability high-impact agroclimatic events include heatwaves in Europe (2003; Black et al. 2004) and Russia (2010; Grumm 2011) as well as drought in Australia (2001–2009; Van Dijk et al. 2013) and Europe (2018; Toreti et al. 2019a).

The growing demand for scientific information on the impacts of climate extremes is a recent trend (Cogato et al. 2019), particularly evident in agricultural outlook reports. Amid other stressors of interconnected food systems, such as population growth, environmental degradation, trade disputes and livestock and human pandemics, and in a rather grim global future where higher risk of hunger and lower nutritional quality are projected (Powell and Reinhard 2016, Tsigchelaar et al. 2018), the risk of extreme events is expected to increase simultaneously with food-supply instabilities in $\geq 1.5$ °C warming scenarios (IPCC 2018). On this account, the asserted impediment extreme events pose to achieving or maintaining food security has spurred a voluminous literature in recent years (see, for example, Zampieri et al. 2020). By examining information on climate and crop-yield anomalies using statistical and simulation approaches, numerous studies contemplated detrimental impacts on yields (Deryng et al. 2014, Powell and Reinhard 2016, Villoria and Chen 2018, Li et al. 2019, Ubilava and Abdalrahimi 2019, Vogel et al. 2019). The potential impacts on commodity market behaviour, nevertheless, is underrepresented (Burkholz and Schweitzer 2019, Chen and Villoria 2019, Chatzopoulos et al. 2020).

Climate change is progressively linked to changes in the occurrence, frequency and intensity of natural disasters in many regions (IPCC 2012). Increasing vulnerability of agriculture to extremes has been not only demonstrated historically and regionally but also projected globally (Deryng et al. 2014, Zhu and Troy 2018, Trnka et al. 2019, FAO, IFAD, UNICEF, WFP and WHO 2021). Past 10-year return events affecting maize production, for example, may become normal at the 1.5 °C warming level by 2030 (Zampieri et al. 2019). In order to disentangle the potential impacts of climate extremes on regional and global food markets and prices, the need to simulate simultaneous and repetitive events in an evolving and interconnected world emerges (Hochrainer-Stigler et al. 2019, Toreti et al. 2019b).

This article contributes to filling that gap by exploring the recursive-dynamic behaviour of food supply and demand under simulated climate extremes from 2020 to 2030. More specifically, we quantified the consequences of concurrent and potentially recurrent crop-yield stress on regional and global production, consumption, trade, stocks and prices. We pursued this assessment by means of incorporating a recently developed nonparametric indicator of compound heat and water stress into a global simulation model of agricultural markets and policies. We designed and run 1000 sets of scenarios where key crops (wheat, maize, rice and soybean) may ‘suffer’ stochastically in space and time while agricultural markets endogenously adjust to rediscover their equilibria. Market responses in 87 key region-crop combinations (appendix A.2) were analysed and synthesized into pure market risk and vulnerability indicators based on a categorization of extreme events into hazardous and non-hazardous. This article expands upon previous work on deterministic simulations of single-case events (Chatzopoulos et al. 2020) by adding to the analysis more markets, partially stochastic space and time dynamics and a risk-assessment component.

Our analysis adopts two innovative aspects in the context of large-scale impact studies. First, we examined the impacts of concurrent and recurrent extremes beyond crop yields, which is where assessments of this type typically stop. We considered the repercussions of climate anomalies on the global system of interconnected agricultural economies and food markets. For example, if the Russian heatwave of 2010 were to recur, alone or with concurrent extremes elsewhere, markets would adjust in and outside the country based on (reasonably-parameterised) national self-interests and policies. The second innovative aspect pertains to the formal quantification of agricultural market risk brought about by extreme events. By treating the frequency values of simulated climate (input) and economic (output) data as approximations of their probabilities, we ranked countries based on the vulnerability and risk their commodity markets may face, be it physical (e.g. production loss), economic (e.g. prices) or socioeconomic (e.g. self-sufficiency).

The remainder of this article is organized as follows. Section 2 lays out the methodological details of the simulation experiment. These include the representation of climate anomalies, calibration of the economic model, design of scenarios, and a conceptual framework for the implementation of vulnerability and risk analysis in the context of agricultural commodity markets. Results are

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4 Marketing years (e.g. 2020 refers to 2020/21).
presented in section 3 and conclusions are drawn in section 4.

2. Methodology

2.1. Representation of agro-climatic anomalies
The Combined Stress Index (CSI) is an indicator built on heat and water stresses that induce crop-yield anomalies (Zampieri et al 2017). It is based on a linear superposition of two other nonparametric indices and country-level crop yields by calibrating the parameters of the former on the latter:

\[
\text{CSI}_{r,c,t} = \hat{\alpha}_{r,c} \times \text{HMDI}_{r,c,t} + \beta_{r,c} \times \text{SPEI}_{r,c,t}
\]

where HMDI is the Heat-Magnitude-Day Index that captures temperature anomalies, SPEI is the Standard Precipitation-Evapotranspiration Index that quantifies persistent water anomalies, and \( r, c, t \) are region, commodity and year identifiers, respectively. Coefficients are ridge-regression estimates that reflect the relative contribution of each stressor to historical yield anomalies (1980–2010). By construction, positive CSI values indicate yield reduction due to single events, such as a heatwave, or combined events, such as a heatwave and drought. Negative CSI values denote beneficial biophysiology leading to higher-than-expected yield. Extreme CSI values were shown to correspond to the most pronounced historical yield anomalies, while values around zero reflect ‘normal’ agro-climatic conditions (i.e. yields lingering around their baseline trends). Equation (1) was applied to wheat, maize, soybean and rain-fed rice. For paddy rice, a river-discharge index was used in place of the SPEI (Zampieri et al 2018). The calculation of CSI values is based on de-trended and standardized data, and so the resulting time-series are decoupled from mean climate change. The overall attractiveness of this index lies in the coverage of multiple attributes related to extremeness such as the occurrence, frequency and amplitude of stress episodes in predefined crop-growing areas and agronomically consistent and crop-specific time windows.

In order to consider the probability of (simultaneous) events that have or may not have occurred—but could occur—at given locations, we adopted a complex multivariate-copula approach. First, all CSI time-series were analysed in terms of mutual dependence using Spearman rank-based correlation. The resulting cases were grouped into two categories: those that exhibited agro-climatic dependence for the same crop and those that did not. Based on the reference period, 1000 alternative CSI sets were then generated for each relevant region-crop pair and simulation year of the economic model under stationarity assumptions (appendix A.3). Dependent-CSI cases were simulated with bivariate (e.g. Nelsen 2006, Genest and Favre 2007) or multivariate regular-vine copulae (Bedford and Cooke 2002, Aas et al 2009, Dissmann et al 2013), while independent-CSI cases were parametrically simulated by inferring either a Gaussian or skew-normal distribution based on the Shapiro–Wilk normality test. The resulting sets of CSI time-series encompass a comprehensive range of possible growing conditions and extremes in either direction.

As large-scale heatwaves and droughts often span continuous surfaces, a number of significantly positive correlations were found in countries that are adjacent or belong in the same agro-climatic zone. Examples of moderate-to-high positively dependent climate stress include Kazakhstan and Russia (wheat), Brazil and Paraguay (maize), Canada and the US (soybean) and China and India (rice). Moderate correlations involving countries from different hemispheres or cases with no obvious teleconnection were also found (appendix A.4).

2.2. Representation of the agricultural sector and markets
Aglink-Cosimo is a global recursive-dynamic partial-equilibrium model of agricultural commodity markets\(^5\). The model is primarily known for its use in generating medium-term agricultural projections published annually (e.g. OECD/FAO 2019, European Commission 2020). Based on the submission of structured questionnaires by national agencies the Organisation for Economic Co-operation and Development (OECD) and the Food and Agriculture Organization of the United Nations (FAO) jointly and annually parameterise and validate status-quo and expected agricultural policies as well as market and trade developments. The resulting medium-term consensus (baseline) serves as reference for the implementation of counterfactual policy-relevant scenarios as well as for calibration of other large-scale models. The platform is developed and maintained by the OECD and FAO Secretariats with defined user groups and contributing institutions, such as the Joint Research Centre of the European Commission.

Aglink-Cosimo is driven by trends, empirically determined elasticities conforming to microeconomic theory and the translation of economic logic, market expertise and expectations into equations and projections. It covers 90+ commodities (incl. meats, dairies, sugar, biofuels), 40 world market clearing prices, and currently simulates detailed supply and demand until 2030. It consists of over 35 000 behavoioural equations, linear or linearized, calibratable and identities, that solve as a problem of nonlinear programming with discontinuous derivatives. Markets for agricultural commodities are competitive and typically clear on prices both at the domestic level,

\(^5\) ‘Recursive-dynamic’ refers to the determination of endogenous variables in each projected year in a unidirectional sequence. The ‘partial-equilibrium’ condition means that only agricultural markets attain equilibrium. Non-agricultural variables are exogenous.
where total supply equals total demand (equation (2)), and at the world level, where net trade is zero (equation (3)):

\[
PP_{r,c,t} \text{ subject to } QP_{r,c,t} + IM_{r,c,t} + ST_{r,c,t-1} = QC_{r,c,t} + EX_{r,c,t} + ST_{r,c,t}
\]

(2)

\[
WP_{r,c,t} \text{ subject to } \Sigma(EX)_{c,t} = \Sigma(IM)_{c,t}
\]

(3)

where PP is the market (producer) price, QP is production, QC is consumption (food, feed, biofuel and other uses), IM is total imports, EX is total exports, ST is ending stocks (public and private) and WP is a world-reference price. Modelled commodities are viewed as homogeneous goods, and total imports and exports are determined separately. Price transmission is indirect in the trade equations through market-integration elasticities that reflect the degree to which domestic and international prices co-vary with one another. Domestic markets trade with the ‘rest of the world’, not bilaterally. Oil prices and macroeconomic factors, such as gross domestic product, inflation, exchange rates and energy prices, as well as population are exogenous and therefore remained unchanged in our experiment. For details see Araujo-Enciso et al (2015) and the sources therein.

2.3. Coupling and calibration

Crop yields in Aglink-Cosimo are modelled endogenously as a function of time, economic drivers and policy instruments:

\[
\ln\text{YLD}_{r,c,t} = \hat{\gamma}_{r,c} \times T_{r,c,t} + \hat{\delta}_{r,c} \\
\times f(PP_{t-1}, ICS_{t-1}, DP_{t-1})_{r,c} \\
+ \text{calib}_{r,c,t}
\]

(4)

where PP is the domestic producer price, ICS is an index of production-cost shares of tradable and non-tradable inputs (e.g. seed, fertiliser, energy) and DP denotes any direct payments affecting area or yield. The linear time-trend component (T) is a proxy for Hicks-neutral technological change. Lags of prices and other variables are included on the right-hand side to parameterise cobweb-like dynamic market adjustments. Crop-production decisions at t, for example, are mainly based on the structure of prices, costs and demand from t-1. The index of costs, which is used as a price deflator, takes into account input quantities in the planting year (t-1) and the harvesting year (t). Yield-to-price elasticities are a composite of economic theory, ad-hoc empirical estimation and expert judgement. Equation-specific intercepts and error terms serve calibration purposes.

In order to incorporate the stress index into Aglink-Cosimo, the yield-CSI association was estimated with the nonparametric approach that was used to originally develop the CSI (Zampieri et al 2017). This led to n locally weighted scatterplot smoothing regressions with a bandwidth of 0.75 per region-crop pair for the period 1980–2010 (16 ≤ n ≤ 31, subject to data availability). The resulting smoothed yields were then linearized to obtain yield-to-CSI coefficients (appendix A.5) and the CSI effect was incorporated into equation (4) through a linear additive predictor.

Upon setting the CSI values equal to zero over the projection horizon, the extended Aglink-Cosimo model was calibrated so as to reproduce the publicly available OECD/FAO (2019) baseline (appendix A.6) that assumes ‘normal’ agro-climate without an explicit agro-climatic parameterisation. This approach allowed for the implementation of exogenous CSI shocks in any particular year by replacing the zero-with non-zero-CSI values and rerunning the calibrated model. The main difference between this approach and the usual implementation of exogenous yield shocks pertains to attribution. The ‘yield-shock approach’ assumes that unfavourable weather is the main reason for low crop yields, often on the basis of subjective judgement and without an empirical justification of the spatiotemporal attributes of the underlying climate conditions. In our approach, yield response remains endogenous and is empirically attributable to climate stress.

It is important to note that carrying out an extensive validation of a forward-looking model like Aglink-Cosimo in the context of this study would be a highly demanding task. Expectations regarding the establishment of food and trade policies and their potential effects often change from year to year, what leads to frequent—but centrally managed and consolidated—changes in the parameterization of the model. Despite this peculiarity, previous validation exercises carried out by the authors in similar settings revealed that the model is able to reproduce quite accurately selected market responses and price spikes stemming from large yield orCSI shocks. At the same time, slight deviations could be explained by concurrent events or policies that are not explicitly—or at least endogenously—modelled (see OECD/FAO 2013, Box 1.1, Chatzopoulos et al 2020).

2.4. Scenario setting and model mechanics

The simulation experiment covered 87 crop-CSI combinations in regions that account for up to 98% of global crop production and exports and up to 93% of world imports. 1000 partially-stochastic runs were performed, one for each set of exogenous and concurrent CSI configurations, where annual market balances were solved recursively-dynamically for all countries over the projection period (2020–2030). Concurrence and recurrence arise from the copula design of partially stochastic CSI_{r,c} draws and the recursive-dynamic nature of the model, where supply and demand are brought to equilibrium for all region-commodity pairs simultaneously in a given year and sequentially in all projection years.
An exogenous CSI shock in the first simulation year \( (t_{sim1} = 2020) \) translates into an endogenous crop-yield response that is steered by the CSI coefficient. The yield effect at \( t_{sim1} \) operates as an equiproportional production (harvest) loss over planted acreage with no area adjustment\(^6\). The climate anomaly is then transmitted to the other elements of equation (2) while the market is searching for a new price equilibrium that satisfies the balance condition. A new domestic producer price is induced by those changes that, along with any simultaneous changes in other markets, countries, and price transmission, contribute to a new global market situation satisfying equation (3). Beyond \( t_{sim1} \), the recursive-dynamic nature of the model makes sure that shocks are implemented on top of the temporally transmitted impact; that is, producers dynamically adjust supply (incl. area) to new price incentives and evolving demand while new events simultaneously exacerbate or moderate the expected market outcome. All in all, climate anomalies are transmitted over crops, countries and time through direct and indirect, current and lagged, and own- and cross-commodity effects altogether affecting market balances and clearing prices, which endogenously adjust at the domestic and world levels.

2.5. Vulnerability and risk from hazardous extremes

Originally proposed in Van Oijen et al (2013) for ecosystems, this section presents a formal framework for probabilistic risk analysis in the context of agricultural commodity markets. The usual region, crop and year subscripts apply but are omitted below for ease of presentation. Crop markets comprise the ‘system at risk’ due to damaging agro-climate. ‘Elements at risk’ are the endogenous solutions of equation (2), henceforth denoted with a placeholder. The probability distributions of the stress index, \( P(\text{CSI}) \), and the elements at risk, \( P(\bullet) \), are linked through the law of total probability:

\[
P(\bullet) = \int P(\text{CSI}) P(\bullet|\text{CSI}) \, d\text{CSI}.
\] (5)

Normal agro-climate, \( E(\text{CSI}) \), leads to the expected state of the agricultural system that is represented by baseline projections of the market variables at risk, \( E(\bullet) \). Hazard (H) can be defined through the CSI as:

\[
H = P(\text{CSI} > 0).
\] (6)

The difference in the system’s expected behaviour under hazardous (\( \text{CSI} > 0 \)) and non-hazardous (\( \text{CSI} \leq 0 \)) conditions, then, reflects its general sensitivity, which we define as vulnerability (V):

\[
V(\bullet) = |E(\bullet|\text{CSI} > 0) - E(\bullet|\text{CSI} \leq 0)|
= \int \bullet P(\bullet|\text{CSI} > 0) \, d\bullet - \int \bullet P(\bullet|\text{CSI} \leq 0) \, d\bullet.
\] (7)

Equation (7) gives a differential picture of the climate-driven market impact between the two subsets. Risk (R), then, can be defined as the product of hazard and vulnerability:

\[
R(\bullet) = H \times V(\bullet)
\] (8)

where \( H \) is dimensionless and \( R(\bullet) \) and \( V(\bullet) \) are measured in the unit of the impacted variable\(^7\).

Interest often lies more on damaging than beneficial conditions. For this reason, we shift our focus to extremely hazardous climate anomalies i.e. rare events with devastating crop-yield potential by arbitrarily defining any CSI value higher than the 90th percentile as extreme hazard; i.e. \( \text{XH} = P(\text{CSI} > 90) = 0.1 \). Given the reference climate conditions, this threshold points to simulated extremes with a return period of one in 10 years, on average, which is analogous to the length of the projection horizon in Aglink-Cosimo. Therefore, the domestic market risk attributable to extreme agro-climatic stress can be defined as:

\[
R(\bullet) = 0.1 \times \left\{ \int \bullet P(\bullet|\text{CSI}\geq 90) \, d\bullet - \int \bullet P(\bullet|\text{CSI} \leq 90) \, d\bullet \right\}.
\] (9)

A numerical and graphical example of calculating the elements of equation (9) is shown in appendix A.7. In the absence of a global CSI, subsets of international prices—which are the culmination of pronounced extremes—were used to define risk at the global level:

\[
R(\bullet) = 0.1 \times \left\{ \int \bullet P(\bullet|\text{WP}\geq 90) \, d\bullet - \int \bullet P(\bullet|\text{WP} \leq 90) \, d\bullet \right\}.
\] (10)

\( V(\bullet) \) and \( R(\bullet) \) can be defined in absolute or relative terms depending on the expression of conditional expectations. In this study, we express \( V(\bullet) \) in physical terms (Mt) and \( R(\bullet) \) in relative terms (%, percentage points)\(^8\). Therefore, \( V(\bullet) \) shows vulnerable quantities while \( R(\bullet) \) reflects relative market

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\(^6\) This assumption is a result of the model structure (harvested acreage = planted acreage) and the CSI design, which measures the yield effect without a decomposition to production and area effects.

\(^7\) In the absence of actual spatial information in the model, the same global level of exposure (area planted) was assumed.

\(^8\) Mt: Megatonne.
risk. Note that since we focus on damaging extremes, displayed \( V(\bullet) \) values imply a reduction in domestic production, exports, ending stocks and an increase in imports and prices. Consequently, \( R(\text{QP}) \) and \( R(\text{PP}) \) can be interpreted as downside production risk and upside price risk, respectively.

### 3. Results

#### 3.1. Extreme climate distorts expected market equilibria

Figures 1 and 2 provide an overview of vulnerability and risk on key wheat and maize markets in 2030. With the exception of plots referring to production, which include countries directly affected by extreme events by design, plots depicting other market elements may include cases with minimal production that are affected indirectly through trade and price transmission. As for soybean and rice markets see appendix A.8, 9.

At the 0.1 hazard probability level, 14 wheat-growing regions displayed production vulnerability ranging from a staggering 18 Mt (Russia) to 1 Mt (UK). Wheat production was also found particularly vulnerable in the EU and Australia (9 Mt each), India and Canada (7 Mt each), China (6 Mt) and Kazakhstan (4 Mt). Lower production potential generally limits prospective absolute damage, and so vulnerability in other key producers, such as Ukraine and Pakistan, was below 4 Mt. Regarding maize production, the US displayed noteworthy vulnerability (85 Mt) followed by China, Brazil (18 Mt each) and the EU (11 Mt). Notable cutbacks were also detected for Argentina, South Africa, Indonesia and Ukraine (4–5 Mt each). Soybean production appeared particularly vulnerable in Brazil (15 Mt) and Argentina (10 Mt) and to a lesser extent in the US (6 Mt), while it amounted to ∼1 Mt in various other countries (e.g. India, China, Ukraine, Paraguay). Vulnerability of rice production equalled or exceeded 1 Mt in four Asian countries (India, China, Vietnam, Philippines). Overall, a number of wheat- and rice-growing regions appeared moderately vulnerable while few maize and soybean producers displayed higher vulnerability due to geographical concentration.

The potential impact of simulated climate extremes was pronounced on trade, which appeared more vulnerable (and riskier) than stocks or consumption in 80% of the markets examined. In terms of exports, high vulnerability was found in the US (50 Mt, mostly maize), Brazil (27 Mt of maize and soybean), Russia (17 Mt, mostly wheat), Argentina (15 Mt, mostly soybean), Australia (9 Mt of wheat), the EU (8 Mt of wheat), Ukraine (7 Mt), Canada (5 Mt of wheat) and India (4 Mt, mostly rice). With regard to imports, on the other hand, the EU appeared to be rather vulnerable (9 Mt, mainly maize) followed by Indonesia (3 Mt, mostly rice), China, Iran, Mexico, Philippines and Turkey (2 Mt each, mostly maize and wheat). A few nonnegative net-trade balances (i.e. exports ≥ imports) in the deterministic baseline turned into negative when moderate-to-severe climate stress was simulated. The highest conditional probabilities of such net-trade position shifts occurring, given that negative supply shocks had occurred domestically, were found to be 95% for wheat in Turkey, 63% for maize in Canada, 43% for soybean in Russia and 18% for rice in Brazil. Those balance changes were driven primarily by higher imports, though some predominantly low exports vanished too. Examples of the latter include Turkey and Pakistan (wheat), Kazakhstan and South Africa (maize), India, Russia and South Africa (soybean) and Brazil (rice). National net-trade losses amounted to ≤1 Mt throughout with the exceptions of wheat in Turkey and maize in South Africa (∼2.4 Mt each). Stocks were found particularly vulnerable in India, China (wheat and rice) and the US (maize and soybean) while consumption was significantly impacted in India (wheat, rice), the US and China (maize) as well as Brazil (soybean).

Trade seems to have shown the higher relative importance in rebalancing global agricultural commodity markets followed by stocks and consumption. Domestic supply shocks generally dictate lower export demand and higher import demand, which in the experiment led to global net-trade decrease. However, part of the foregone trade was compensated with trade diversion, lower tariff barriers and second-order effects (e.g. favourable supply shocks) elsewhere. Stocks come in (fixed) from the preceding year and are released for domestic consumption to alleviate the impact of domestic deficits and reduced global trade. As expected, this compensation was partial in the experiment, too; when aggregate stocks fall to minimal feasible levels due to concurrent harvest losses, prices become even more sensitive to recurrent shocks, poorer consumers reduce their calorie consumption incurring the costs of malnutrition, and less grain remains available for feed. Global consumption, which dropped too, generally seems to be less flexible than trade and aggregate stocks in rebalancing market positions as grains are already highly substitutable in the global market for calories.

Inspection of the trajectories of potential market outcomes revealed that climate extremes may severely disrupt crop supply and lead to record-breaking figures in any particular year until 2030.

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9 Calculated as \( P(\text{IM}_{\text{base}} > \text{EX}_{\text{sim}} | \text{CSI}_{\text{sim}} > \text{CSI}_{\text{base}}) \) for each region-commodity pair where baseline exports were equal to or greater than baseline imports in 2030.

10 Import tariffs and export taxes are endogenous for Canada, China, the EU, Japan, Russia, South Korea, the US and exogenous in all other cases.

11 Using the period 2000–2020 as reference.
Figure 1. Vulnerability and risk in domestic wheat markets due to concurrent and recurrent extremes at the world level, 2030. Panels (a) and (b) show the most vulnerable (Mt) and riskiest (%) markets per supply and demand element due to extremely damaging agro-climatic anomalies at the 0.1 probability level (i.e. occurring once every 10 years, on average). Vulnerability measures the sensitivity of the domestic market system to extremes (i.e. the difference between the mean market outcome from extremely hazardous conditions and the mean market outcome from all other conditions). Similarly, risk measures relative distance between the two subsets. Both indicators are measured in absolute terms (i.e. hazardous extremes imply reduction in all displayed market elements but imports, which increase). Panel (c) shows a qualitative ranking of markets by combining their vulnerability and risk into grids with colours arbitrarily separated at mid-points to isolate highs and lows. Results based on 1000 sets of recursive-dynamic simulations of annual market outcomes under partially stochastic agro-climatic configurations from 2020 to 2030. As for soybean and rice markets, see appendix A.8, 9.

Record-high producer prices were detected in 87% of the examined markets, while clearing prices in the remaining cases approached their historical peaks. In general, although spikes in international prices are correlated with price spikes in—well integrated—key exporters, the risk of higher producer prices appeared higher in importing countries, such as Iran, Pakistan, South Africa, Kazakhstan and India (figure 3(a)). In their vast majority, elevated prices coincided with at least record-low self-sufficiency or record-breaking dependence on imports, occasionally combined with record-low stock-to-use ratios. Overall, positive cross-commodity substitution effects led to higher prices of low-protein feed substitutes, such as coarse grains, cereal brans, dried beet pulp, molasses, beet roots and tubers, as well as higher consumer prices throughout.

Higher global prices were the culmination of pronounced regional extremes (figure 3(b)). Maize and soybean exhibited record-peaks at 311$/t (63%
Figure 2. Vulnerability and risk in domestic maize markets due to concurrent and recurrent extremes at the world level, 2030. Panels (a) and (b) show the most vulnerable (Mt) and riskiest (%) markets per supply and demand element due to extremely damaging agro-climatic anomalies at the 0.1 probability level (i.e. occurring once every 10 years, on average). Vulnerability measures the sensitivity of the domestic market system to extremes (i.e. the difference between the mean market outcome from extremely hazardous conditions and the mean market outcome from all other conditions). Similarly, risk measures relative distance between the two subsets. Both indicators are measured in absolute terms (i.e. hazardous extremes imply reduction in all displayed market elements but imports, which increase). Panel (c) shows a qualitative ranking of markets by combining their vulnerability and risk into grids with colours arbitrarily separated at mid-points to isolate highs and lows. South Africa is presented arbitrarily at #1 in terms of risk of higher imports because the latter turn from zero (baseline) into positive. Results based on 1000 sets of recursive-dynamic simulations of annual market outcomes under partially stochastic agro-climatic configurations from 2020 to 2030. As for soybean and rice markets, see appendix A.8, 9.

3.2. Recurrent extremes induce higher market uncertainty over time

Agriculture experiences lags between the time production decisions are made and the output is produced, distributed and consumed. Such delayed demand signals sent to crop producers, whose expected behaviour (of adjusting production to demand) was modelled with lagged prices and costs, would theoretically result into ‘fan’ shapes. Although...

vs baseline) and 700$/t (45%) that coincided with record-low stock-to-use of 0.135 (−25%) and 0.077 (−25%), respectively. Wheat and rice prices rose to a lesser extent (34%, at 325$/t; 10%, at 529$/t) with a simultaneous stock-to-use reduction of −8% (at 0.367) and −7% (at 0.291), respectively. With the exception of soybean, all other crops exhibited record-high global import dependence ranging from 0.11 to 0.26.
Figure 3. Price risk and uncertainty in global crop markets due to concurrent and recurrent extremes at the world level. Panel (a) shows the riskiest (%) domestic producer prices due to extremely damaging agro-climatic anomalies at the 0.1 probability level (i.e. occurring once every 10 years, on average) and can be interpreted as upside price risk (i.e. the difference between the mean market-clearing price from extremely hazardous conditions and the mean market-clearing price from non-hazardous conditions). The dotted line marks upside risk in world reference prices. Panels (b) and (c) focus on overall price uncertainty including beneficial extremes. Fan charts (b) display ranges of possible trajectories. Scatterplots (c) show the year-on-year range and standard deviation of simulations (quadratic fit). World reference prices are: No. 2 hard red winter wheat, USA FOB Gulf Ports (June/May); No. 2 yellow maize, USA FOB Gulf Ports (Sep./Aug.); USA soybean, CIF Rotterdam (Oct./Sep.); and 100% milled rice, grade b, nominal quote, Bangkok FOB (Jan./Dec.). Results based on 1000 sets of recursive-dynamic simulations of annual market outcomes under partially stochastic agro-climatic configurations from 2020 to 2030.

the stationarity assumption governing the data-generating process of stress events masks such variability (figure 3(b)), the inspection of interannual variability statistics provided a clearer picture: uncertainty in all endogenous prices increased progressively in a nonlinear fashion (figure 3(c)). At the world level, soybean and maize had the highest range (410 $/t and 177 $/t), on average, followed by rice and wheat (≤ 149 $/t). The same held for standard deviation (53 $/t for soybean, 24 $/t for maize, ~15 $/t for rice and wheat). While soybean showed the highest annual growth in the range (15 $/t), standard deviation grew by ~0.4 $/t/year for all crops.

Global prices were leptokurtic and highly right-skewed for maize, moderately skewed for wheat and fairly symmetric for soybean and rice. Global price skewness increased slowly and nonlinearly over time mimicking to a large extent the skewness of clearing prices in key exporters. Most domestic prices displayed increasing skewness for maize and soybean (exc. the EU, India, South Africa) and decreasing for wheat and rice (exc. China, India, Pakistan, Russia). The medians of simulated prices lingered around their deterministic (baseline) counterparts (± 9 $/t).

3.3. Concurrent extremes lead to extreme global prices
The importance of simultaneous regional extremes in crop-price formation at the global level can be understood by looking at the agro-climatic configuration in those simulations where world prices reached their peak. From this perspective, the principal origin of extreme wheat prices was unfavourable climate conditions in Russia (30/50 cases; figure 4), be it alone or concurring with stress events.
Figure 4. Extreme world prices attributable to concurrent and recurrent climate stress at the world level, 2030. Red and yellow grids denote extremely damaging (CSI > p90) and weak-to-severe (p90 ≥ CSI > 0) climate stress, respectively, during the corresponding growing season. Green indicates average or beneficial agro-climate (CSI ≤ 0). The CSI is an indicator built on heat and water stresses that induce crop-yield anomalies. Reading the grid charts by row indicates domestic conditions across sets of simulations where world prices were extremely high (x-axis). Reading the grid charts by column shows the agro-climatic configuration across key markets (y-axis) for any particular set of simulations that led to an extremely high world price. Therefore, horizontal concentration of non-green grids points to cases where domestic (simulated) events may have a high global impact, while vertical concentration of non-green grids reflects the importance of concurrent events. Underlying reference prices are: No. 2 hard red winter wheat, USA FOB Gulf Ports (June/May); No. 2 yellow maize, USA FOB Gulf Ports (Sep./Aug.); USA soybean, CIF Rotterdam (Oct./Sep.); and 100% milled rice, grade b, nominal quote, Bangkok FOB (Jan./Dec.). Markets sorted by descending historical production (2015–2019). Results based on 1000 sets of recursive-dynamic simulations of annual market outcomes under partially stochastic agro-climatic configurations from 2020 to 2030.

in other key exporters (the EU, the US, Canada, Australia, Kazakhstan). Interestingly, favourable conditions in many other countries did not appear to alleviate an explosion of world prices attributable to extremes at least in Russia. Climate anomalies in the EU also affected global prices, alone or with concurrent severe or extreme events in the US and Canada.

Damaging extremes in the US dominated in simulations that resulted in skyrocketed maize prices as the US makes up the lion’s market share in global production and exports. Concurrent events in Brazil and Paraguay in the same or opposite direction did not appear to attenuate the impact on world prices, though the corresponding domestic impacts were pronounced. High soybean prices, on the other hand, arose due to extremes mostly in Brazil (24/50 cases), Argentina or Paraguay (21/50 each) and less so in the US (16/50). Concurrent events across the Americas, largely between Brazil-Paraguay but not only, that coincided with events in key importers such as China and India, also played a role.

Extremes in India appeared to drive high rice prices at the world level (36/50 cases). Similar to the case of Russian wheat, beneficial conditions in other big producers, such as China, Indonesia and Thailand, only partially compensated for global price spikes attributable to simulated extremes in India. Concurrent severe-to-extreme events in top rice producers also mattered, for the most part in Indonesia, Vietnam and Thailand.

Although extreme market outcomes generally stem from extreme climatic conditions, it is important to note that concurrent weak-to-severe (but not extreme) events across regions may also have a significant global impact, albeit at a lower probability rate. A close examination of the 90th percentile—that is, extending the grid charts of figure 4 to the left—revealed that combinations of weak-to-severe CSI values led to extreme world prices in six out of 100 cases per crop, on average. Maize prices, for example, were 18%–29% higher than expected (vs the maximum change of 63%) due to concurrent moderate events in the Americas, China and India, while rice prices...
were 6% higher (vs the maximum change of 10%) due to concurrent moderate events in India, Japan and Vietnam.

### 4. Conclusions and recommendations

In this article we assessed the impacts of concurrent and recurrent climate extremes on global agricultural commodity markets. Having calibrated a partial-equilibrium model with an index that attributes country-level crop-yield anomalies to climate anomalies, we simulated the market impact of 1000 alternative configurations of heat and water stress from 2020 to 2030. Focusing on detrimental events, such as heatwaves, droughts and overwet conditions, and subsets of supply and demand elements at equilibrium, we analysed climate-input/market-output relationships in a formal risk-assessment framework through the concepts of hazard (climate stress), vulnerability (market sensitivity) and risk (hazard \times vulnerability).

Our findings suggest that regional climate extremes could alter crop availability and considerably distort domestic and global markets in any particular year until 2030. Simulated international prices exhibited not only increasing uncertainty over time but also record-peaks that coincided largely with unusually low stock-to-use and record-high import dependence. Although the impacts on global markets were more pronounced in cases where key exporters suffered large harvest losses, importing and developing economies—hit domestically or through exposure to international prices—seemed to exhibit higher upside price risk. This is not surprising since in developing economies many households spend a large share of their income on staple foods (i.e. food demand is more elastic). As a result, while developed economies may lose or gain market shares, importing and developing countries could increasingly face lower self-sufficiency and price destabilization. Consequently, climate extremes could further slow progress towards achieving global food security by exacerbating variability in commodity markets (see Sustainable Development Goals—Target 2.1).

Climate-driven food-supply shortfalls in our simulation experiment were addressed and through dynamic local adjustments and trade. Shocks were partly absorbed domestically by endogenously lowering production, changing consumption and ‘tapping’ on reserves, partly transmitted to other countries through trade and partly compensated with favourable yield shocks elsewhere. Although this inherent interdependence of the various market elements could enhance the importance of anticipatory food policy responses, it is not easy to tackle in the real world. While substantial increases in crop production will be necessary to meet the needs of growing human population in the coming decades, some countries may not be able to sustainably expand production (Carr et al 2016). Furthermore, trade diversion and the release of private and public private stocks may mitigate market uncertainty when crop yields plummet—in reality and model-wise—but their interaction may trap countries in risk-averse or risk-taking behaviour. On the one hand, creating and sustaining public reserves to absorb yield losses and the resulting price volatility may be difficult in practice (Thompson et al 2012, Lassa et al 2019), and on the other, increasing reliance on imports from countries with established reserves entails the risk of propagation of negative effects when the latter suffer cutbacks or choose to restrict food supply (Fader et al 2016, Marchand et al 2016, Chen and Villoria 2019).

In interpreting our results four important remarks ought to be made. First, in an effort to capture major variability in concurrent events and link them with global food markets, the CSI simulations used herein are based on well-documented records of historical events. Therefore, simulated climate-stress distributions do not serve as a surrogate of all possible future events. As historical data and climate projections are being updated, new hazards may be identified and additional regions may be exposed. Furthermore, future applications of our proposed risk-assessment method with this or other large-scale agro-economic models can rely on projections of extreme crop yields, albeit with the loss of attribution to specific stressors. Second, initial conditions matter in economic simulation models. In fact, market vulnerability and risk due to climate extremes are associated not only with the occurrence of such events but also with conditions that may facilitate or impede certain market developments, particularly in the short term. Livestock or human pandemics such as the African Swine Fever and COVID-19, for example, would likely alter at least short-term market vulnerabilities and risks. Third, uncertainty pertaining to model structure—essentially variability in (non-)modelled economic or biophysical processes—poses a common pitfall in economic analyses of this type. For example, short-term policies applicable in extreme situations such as lower import tariffs were not modelled endogenously for all countries, what may imply overestimation of trade impacts in some cases. Similarly, generally less reliable—albeit perhaps politically justifiable—measures that restrict or ban exports and therefore severely distort international crop markets and erode food security cannot be excluded in reality (see Marchand et al 2016, Swanidze et al 2021). Finally, climate-driven market vulnerability and risk are ‘open’ definitions. While these were explicitly defined herein, the contribution of other factors such as current or future early-warning systems, evolving climatic exposure (e.g. a non-fixed
hazard parameter) and biophysical redundancy (see Fader et al 2016) would be substantially more difficult to assess without further model integrations.

In light of the above limitations, synthesising the complex manifestations of food supply, demand and prices attributable to extreme events can improve information asymmetry across various market participants. Producers and agri-businesses may better evaluate their own exposure and vulnerability to extreme climate and, therefore, assess the need to engage in traditional strategies for on-farm risk control (e.g. tolerant crop varieties, improved soil management, investment in irrigation systems, fine-tuning of crop calendars) or risk-sharing (e.g. insurance, futures markets). The role of governments will be particularly crucial in providing more flexible risk-management tools to producers (see Pieralli et al 2020 for a simulation example, FAO, IFAD, UNICEF, WFP and WHO 2021 for innovative climate-resilience measures). A simulation exercise of this type also provides agricultural market analysts with additional insights on the potential impacts of global climate anomalies on medium-term agricultural commodity prices. The given model granularity also allows for the elicitation of climate-driven market-risk profiles at the country level (see appendix A.10). Such profiles can help planners identify country-crop combinations prone to climate hazards, anticipate potential consequences on local food systems and develop contingency mechanisms to evaluate prospective risks, such as persistent dependence on imports. Last but not least, our results highlight the importance of international cooperation to responding to current or anticipating future food crises at the global level.

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Author contributions

T C conceptualized the idea, built the CSI into the Aglink-Cosimo model, performed the market simulations, analysed the results and wrote the manuscript. I P D contributed to streamlining the manuscript. AT generated the CSI simulations and contributed with text (section 2.1). M A and T C coded the loop of repeated executions of the Aglink-Cosimo model using the CSI simulations as alternative input data. M Z provided the CSI reference data. All authors contributed to the revision and approved the final version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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Disclaimer

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.
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