Agricultural commodity market responses to extreme agroclimatic events

T. Chatzopoulos[1]; I. Pérez Domínguez[2]; M. Zampieri[3]; A. Toreti[3]

1: European Commission, Joint Research Center, Sustainable Resources Directorate, Economics of Agriculture Unit, Spain, 2: European Commission, Joint Research Center, , Spain, 3: European Commission, Joint Research Center, , Italy

Corresponding author email: thomas.chatzopoulos@ec.europa.eu

Abstract:

Economic simulation models typically assume 'normal' growing conditions in eliciting agricultural market projections, contain no explicit parameterization of climate extremes on the supply side, and confound multifarious sources of historical yield fluctuation in harvest-failure scenarios. In this paper we augment a partial equilibrium model of global agriculture with a recently developed compound indicator of agroclimatic stress. We perform a multi-scenario analysis where the most extreme temperature and soil-moisture anomalies of the last decades, both negative and positive, recur in the near future. Our results indicate that extreme agroclimatic conditions at the regional level may have significant impacts both on domestic and international wheat and maize markets.

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Key words: climate extremes; commodity markets; agriculture; simulation

Introduction

Over the last four decades we have witnessed a series of meteorological extremes of unprecedented frequencies, intensities, and duration (IPCC 2012). Especially during the 2000s, the warmest decade on record since 1850, numerous regional and global records were broken (WMO 2013). The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) leaves little room for doubt on the future occurrence of extreme climatic anomalies. Large-scale agrometeorological events, such as the 2003 European heatwave and the 2010 and 2012 droughts in Russia and the US, will *'very likely'* occur more frequently, more intensely, and last longer in many areas (IPCC 2012).

Agroclimatic extremes are increasingly expected to collide with major drivers that already put pressure on the global food system, such as population growth, dietary shifts, environmental degradation, and trade interdependency (Janetos et al. 2017). For this reason, the impacts of adverse crop-growing conditions on food and feed supply gain an honorable mention in agricultural outlook and market reports (e.g., European Commission 2017; OECD/FAO 2017; Chinese Ministry of Agriculture 2016; Trostle 2008). Paradoxically enough, the impacts of extreme events on commodity markets constitute an area considerably under-researched than climate change itself, on which integrated assessments, scenario harmonization, and model inter-comparison have started to make a step change (e.g., Nelson et al. 2014). To our knowledge, there is no peer-reviewed study that assesses the sensitivity of domestic commodity markets to climatic extremes. Furthermore, ongoing work seems to overlook the short-to-medium term effects of regional events and instead place emphasis on the long-term role of global extremes (Bailey et al. 2015; Janetos et al. 2017). Climate extremes and food systems are inherently local, and therefore assessing the long-term market impacts of globally concurrent events pre-requires the understanding of short-term market impacts of recurrent regional extremes.

The aim of this paper is to fill this gap by 'stress-testing' agricultural commodity markets with extreme agroclimatic shocks. More specifically, we set out to quantify the potential domestic and global market impacts of single or combined anomalies that may occur in key wheat and maize growing areas. We pursue this assessment by means of incorporating a recently developed indicator of climatic anomalies into an economic simulation model of global agriculture. We simulate 32 single region-crop-year scenarios to explore the potential short-to-medium-term implications for key domestic and global agricultural markets.

The work underlying this paper adopts two important distinctions in the line of impact studies. First, we implement an innovative method for incorporating an agroclimatic index into a global partial equilibrium model. The potential effects of climatic phenomena on commodity markets are typically inferred through yield or production shocks (Willenbockel 2012; Araujo-Enciso, Pérez Dominguez, and Santini 2015; Bailey et al. 2015; Wiebe et al. 2015; Lunt et al. 2016). The main disadvantage of the supply-shock approach pertains to the inability of 'pure' economic models to isolate the contribution of historical meteorological variability on realized crop yields. Production fluctuations, and thus price variability, are the immediate or lagged result of a mix of short- and medium-term factors, such as speculation, pest or disease outbreaks, domestic policies, structural change, and macroeconomic fluctuations, all on top of changing agroclimate and evolving agricultural systems. For this reason, the frequent interpretation of a historical production drop in a presumably 'dry' season as a production shock due to drought is trivial in the absence of an empirical justification of the spatial and temporal attributes of that drought. In other words, without factoring meteorological data into an economic analysis, the magnitude of production oscillations falls short of explaining the extent of commodity price fluctuations due to extreme agroclimatic events (Baffes and Haniotis 2010). In addition to that, the evolution of agricultural systems over time renders the comparison between simulated impacts based on past production shocks with the actual impacts of those historical shocks, difficult (Bailey et al. 2015). Finally, the supply-shock approach cannot empirically identify the driving meteorology, which is frequently based on subjective judgment (Marx and Weber 2012) and, occasionally, on over-reported media news. The use of an empirical index that translates specific meteorological phenomena into endogenous crop-yield responses within a simulation model disentangles these caveats. Our second contribution pertains to the estimation of crop- and region-specific impact coefficients that quantify historical sensitivity to extremes. These coefficients can be utilized in any global agroeconomic model that contains annual yield or production variables.

Weather and climate extremes can be defined in various ways. Weather extremes generally signify rare and short-lived events, from hours up to several days, with devastating potential. Typical examples include very hot days and heavy precipitation events. Climate extremes represent similar events but viewed over longer periods, such as weeks or months. The index used herein is based on meteorological anomalies that exert biophysical stress over the course of two consecutive months preceding the harvest. Henceforth, we use the term 'climate extremes'. We recognize, however, that the thin line between these terms is attributed to the mutual recursion they exhibit. Extreme weather is a shock within the climate system, and a shift in the climate system changes the way we perceive and define weather and climate extremes (see IPCC 2012, p. 41).

The remainder of this article is organized as follows. A brief introduction of the stress index is given in section 2. Then, we present the estimated impact coefficients, their incorporation into the economic model, backdrop on the simulation scenarios (section 3), and a compilation of results (section 4). We conclude with study limitations and an outline of ongoing work on stochastically concurrent and recurrent extremes (section 5).

2 Background

In the following subsections we describe the agroclimatic index. We then relate its historical variation with international crop prices.

2.1 Combined Stress Index (CSI)

The CSI is a recently developed non-parametric indicator of the most relevant agroclimatic extremes (Zampieri et al. 2017). It is a linear superposition of two other indices over the period 1980-2010: a temperature-anomaly index that captures heat stress and a soil-moisture index that quantifies persistent anomalies in water balance. By construction, a positive CSI value indicates limiting conditions for crop growth that stem from single climatic anomalies, such as a heatwave or a drought, or combined events (e.g., a heatwave and a drought, or a heatwave and soil-water excess). Similarly, negative CSI values denote temperature and soil-moisture anomalies that induce yield improvement. Zero or near-zero CSI values reflect close-to-average growing conditions.

A stylized feature of the CSI is that its counterparts take into account multiple meteorological attributes. Non-zero values, for instance, reflect the *occurrence* of anomalies with respect to the mean. The heat-stress component of the CSI accounts for the frequency and amplitude of abnormally high daily-scale temperatures (*duration* and *intensity*). The CSI is computed for the phenologically critical months of each crop post-planting (*timing*); that is, two months before the harvest of wheat, and four to two months before the harvest of maize. Therefore, the periods of anthesis and grain filling, before and during which the number and quality of grains are immensely sensitive to extremes (e.g., due to parthenocarpy or grain deformation), are explicitly considered. Finally, the CSI focuses exclusively on crop-growing regions and accounts for multiple cropping (*spatial extent*). Overall, the CSI was found to correlate well with inter-annual yield and production variability both at the global (see Zampieri et al. 2017) and regional levels (see section 3 herein).

2.2 Agroclimatic extremes and international crop prices

Agroclimatic variability can be seen as a typical supply shifter that alters the short- to medium-term availability of the affected agricultural commodities. Commodity prices as well as other elements of the economic system (e.g., area allocation, trade) may not settle immediately to their long-run equilibrium; they frequently under- or over-shoot it, following cobweb-like adjustments before the fluctuation intensity theoretically decays (Norwood and Lusk 2008, p. 131). The extent of impacts on a domestic market in a given year depends on the sensitivity of the affected areas and cultivars, the attributes of the extreme event(s) taking place, the status-quo of the market at the time of the shock, and domestic policies (e.g., stockholding). Governmental interventionism also plays a role, as some regions are considered more interventionist than others (Bailey et al. 2015). For instance, following the historically worst drought in the Russian Federation (henceforth 'Russia'), that of 2010, domestic and international prices of wheat rose dramatically after the announcement of the export ban in late summer (Oxley 2012, p. 130).

The extent to which global markets may be affected depends further on the extent of global concurrence of agroclimatic shocks, the positioning of the impacted countries in the trade arena, and the state of world stocks at the time of the shock(s). Assuming stable domestic demand for a commodity, negative climatic anomalies that lead to unfavorable growing conditions translate into a negative domestic supply shock, which ultimately dictates lower domestic export demand and higher import demand. The reverse applies for positive agroclimatic anomalies. Concurrent events convolute the short-to-medium term global picture for two reasons. First, food surpluses and lower prices in one place often compensate for production shortage and higher prices in another (Lybbert, Smith, and Sumner 2014). This is of particular relevance for crops that display latitudinally dispersed production, such as wheat. Positive agroclimatic anomalies in the US, Russia, and Canada in 2009/10, for instance, counterbalanced negative anomalies in the EU, Australia, and Ukraine, thus contributing to a fall in the international price of wheat (figure 1). Second, the coincidence of various factors, such as high energy prices, prioritization of biofuel policies, macroeconomic factors, and trade policy responses to harvest failures render the relative attribution of price fluctuations to adverse meteorology difficult. An example is the 2007/08 crisis that, owing to various economic factors besides adverse growing conditions, has remained in recent economic history as the 'perfect storm' (Trostle 2008; Baffes and Haniotis 2010).

Table 1 lists the key producers and exporters of wheat and maize. We hypothesize that the extent of sensitivity of the global food system to regional extremes depends on the crop(s) and region(s) one may looks at. Without considering cross-price effects, single-country events may affect global wheat prices in rather small amounts, whereas a sudden world price change for maize is more likely to result from extremes in the Americas.

<< Table 1 about here >>

Figure 1, which plots changes in regional CSIs over recent years where notable world price spikes or drops occurred, reveals some interesting insights. First, in every case there have been many producers and major exporters facing climate extremes. Second, the direction of change in the CSIs in three specific regions shows a consistent co-movement with the direction of change in world prices across all displayed (and most non-displayed) years: deteriorated (improved) growing conditions for Russian wheat and US and Chinese maize are consistently accompanied by a rise (drop) in the respective world price. Similar co-movements were also identified for other cases (e.g., Canadian and Ukrainian wheat), albeit in lower frequencies. Third, concurrent agroclimatic anomalies seem to matter more in the case of wheat, probably due to its geographical spread, in which case the number of regions with a large CSI change exceeds those with a low CSI change, thus contributing to a large change in world prices. The extent to which concurrent extremes in key maize regions matter is masked by the dominance of US exports. However, an inter-hemispheric compensation can be ‘eyeballed’ due to the opposite movement of the CSI across certain countries in most years of the sample (see also Lybbert, Smith, and Sumner 2014). Taking all available years into account (1980-2010), the highest positive correlations between changes in the CSIs and world prices were found for US maize (0.59, $p < 0.01$) and Russian wheat (0.42, $p < 0.05$).

<< Figure 1 about here >>

3 Methodology

In the following subsections we present the methodological framework for estimating regional yield-to-CSI coefficients as well as their incorporation into Aglink-Cosimo. We also describe the simulation setup.

3.1 Crop yields and agroclimatic variability

The first step in our analysis was an econometric estimation of the sensitivity of average national yields to agroclimatic variability. This step resulted in impact coefficients that were later plugged into the economic model. For this reason, we developed crop- and region-specific models with first-differenced yield (YLD), production (QP), and the CSI. The estimated structural-equation model (SEM) is of the following form:

(1.1) $\Delta.ln(QP_{c,r,t}) = b_{1,c,r} \times \Delta.(CSI_{c,r,t}) + \varepsilon_{1,c,r,t}$

(1.2) $\Delta.ln(YLD_{c,r,t}) = b_{2,c,r} \times \Delta.ln(QP_{c,r,t}) + \varepsilon_{2,c,r,t}$

where *c*, *r*, and *t* are crop, region, and marketing-year identifiers respectively, QP and YLD are J vectors of observations on total national production (kt) and average crop yield (t/ha), CSI is a J×1 matrix of observations on the CSI, b_1 and b_2 are the QP-to-CSI and YLD-to-QP coefficients, and ε_1 and ε_2 the corresponding J×1 matrices of residuals. QP is endogenous in both equations. The SEM approach tackles this endogeneity with instrumental variables (IV) to produce consistent estimates of b_1 and b_2, and generalized least squares (GLS) to account for error correlation between equations. The use of first-differences and absence of intercepts filter out deterministic and stochastics trends throughout, thus minimizing any potential dependence of the beta coefficients on trends. Intercepts and trends in the relevant yield equations were re-estimated endogenously during calibration of the simulation model at a later step, given the CSI and other economic drivers.

Following the Baron-Kenny (1986) approach, the effect of post-planting agroclimatic variability on yield was estimated indirectly. The direction and value of b_1 show the change of the conditionally expected production due to a marginal change in the CSI, while b_2 shows the change of conditional yield due to a marginal change in production. Therefore, the product $b_1 \times b_2$ is the yield-to-CSI impact coefficient. A direct regression of Δ.ln(YLD) against Δ.(CSI) leads to comparable impact coefficients, but the SEM approach is more efficient in assigning the yield effect to post-planting production changes.[1] Note also that these coefficients reflect the *average* sensitivity of yields over time (1980-2010). This has a very important implication for the simulation experiment: unless the sensitivity of a country has remained stable over time, re-enforcing the most extreme meteorological conditions of the past into the future leads by definition to production and yield changes that do not exceed the magnitude of the corresponding historical changes.

<< Figure 2 about here >>

Levels and ranges of statistically significant impact coefficients for selected regions can be seen in figure 2. Overall, the de-trended SEMs show satisfactory explanatory power the highest of which was found for the case of aggregate EU-15 wheat yields (76%). Highly positive (negative) values in the CSI are associated with a decrease (increase) in average national yields, ceteris paribus. The highest impact coefficients were found for Romanian wheat (-0.062) and South African maize (-0.061), whereas the lowest for Mexican maize (-0.002). Among key wheat exporters, Australian, Canadian, Kazakh, and Russian yields show particularly high sensitivity to agroclimatic variation with their response exceeding the global mean response. US maize yields are slightly more responsive than the global average, while Argentinian yields lie just below. The width of the bars in figure 2 represents the sampling distributions of the impact estimates. It can be seen that the response of wheat yields in Kazakhstan and Russia, as well as maize yields in EUE, can be regarded as particularly uncertain.[2]

A statistically significant effect was not found in some cases even with alternative model specifications and functional forms. Possible reasons for this may include the masking of localized extremes by overall 'normal' meteorological conditions, the non-explicit representation of irrigation in the CSI and national yields, or a highly non-linear relationship between yields and climatic variables that remains subsumed into the short time series. For those cases, coefficients from two global impact functions were used in the simulation experiment.[3]

3.2 Economic model extensions

Aglink-Cosimo is a global recursive-dynamic non-spatial partial equilibrium model of agricultural commodity markets. It is the main modelling tool used in the annual OECD-FAO Agricultual Outlook, which produces medium-term projections for counterfactual policy analysis (OECD/FAO 2017). A similar exercise is carried out at the EU level using the European Commission's version of the model, which extends the released OECD-FAO baseline with EU short-term figures, alternative macroeconomic assumptions, and expectations of market experts (European Commission 2017). Aglink-Cosimo is developed and maintained by the OECD and FAO Secretariats with a defined group of users from national agencies, research institutes, and market experts.

Aglink-Cosimo covers 90+ commodities in 44 countries and 12 regions, and performs supply, demand, price, and trade simulations over a 10-year horizon. The model is trend- and elasticity-driven, and consists of over 43,000 behavioral equations, linear or linearized, that solve as a square system. Supply and demand are balanced both at the domestic and world levels,[4] albeit with no explicit transmission equations. Bilateral trade cannot be directly inferred. Country-specific information on agricultural policies is updated annually in terms of data and parameters to facilitate the modelling of potential market developments. Macroeconomic factors such as GDP growth, inflation and exchange rates, oil prices, and population growth enter the system exogenously.

Crop production in Aglink-Cosimo is an identity equation that equals the product of average regional yield and harvested area (AH):

$$(2) \qquad QP_{c,r,t} = YLD_{c,r,t} \times AH_{c,r,t}$$

Crop yield is generally modeled endogenously as a function of a linear time trend and economic drivers, such as producer prices, subsidies, and shares of input costs:

$$(3) \qquad lnYLD_{c,r,t} = a_{1,c,r} + a_{2,c,r} \times T + f\,(economic\ drivers)_{c,r,t,t-1} + lnR_{c,r,t}$$

The intercept (a_1) and residuals ('R-factors') are inter-dependent calibration parameters; they can be thought of as 'garbage bins' for omitted time-invariant and time-varying factors, respectively. These terms are endogenized (exogenized) during calibration (simulation). Area harvested is determined endogenously within a recently extended system of equations where production incentives for all annual crops are considered simultaneously. For details on the model documentation, see OECD/FAO (2015) and Araujo-Enciso et al. (2015).

The CSI was introduced as a linearly additive predictor in equation Eq. (3). The impact coefficients used in Alink-Cosimo were based on the corresponding SEM estimates.[5] Following a re-estimation of the constant, the trend, and residuals in the yield equations of Aglink-Cosimo, the model was calibrated such that baseline yields (2018-2027) with 'normal' CSI values coincide with the baseline yields from the standard version of the model, which assumes average growing conditions without modelling them explicitly.[6]

The occurrence of agroclimatic extremes at year *t* for a given crop and region causes a yield departure from the baseline, henceforth Δ.YLD, which we express as percent deviation from the baseline value:

$$(4) \quad \Delta.YLD = 100 \times (YLD^{scen} - YLD^{base}) / YLD^{base}$$

where the CSI takes on exogenously its scenario value at *t*, and thus leads endogenously to YLD^{scen}. The overall impact of meteorological variability on crop yield will be beneficial or less damaging if $CSI^{scen} < 0$ (and thus $YLD^{scen} > YLD^{base}$) and damaging or less beneficial if $CSI^{scen} > 0$ (and thus $YLD^{scen} < YLD^{base}$). By construction of the CSI, extremes are assumed to hit regions by surprise after planting. Although the yield change at *t* is a production effect over the baseline area planted, the model structure does allow dynamic area adjustments beyond *t*. Yield and production changes are transmitted to the system through own- and cross-crop effects, thus causing dynamic and endogenous supply, demand, price, and trade adjustments.

3.3 Simulation scenarios

We consider 32 deterministic scenarios based on single region-crop-year extremes.[7] For selected crop-region combinations of table 1, two scenarios were examined: extremely unfavorable and extremely favorable growing conditions. The scenario values were determined on the basis of actual agroclimatic variability over the period 1980-2010. We identified the historical years with the maximum and minimum CSI values per crop and region, which we then used as shock values, one at a time, into the first simulation year (2018/19 marketing year). A scenario setup of this kind does not assume a predefined yield or production change of identical magnitude with the historical one; instead, an exogenous meteorological shock translates into an endogenous yield response based on an empirically established relationship between the two.

4 Results

Figures 3 and 4 depict the potential domestic market effects of extremely unfavorable and extremely favorable agroclimatic conditions. Unless mentioned otherwise, results are presented as percent deviations with respect to the baseline values for the marketing year 2018/19 (see annex tables A1 and A2).

4.1 Domestic wheat markets

Wheat-growing regions display yield reductions of varying magnitude (amber bar portions). Kazakhstan, Australia, Russia, and Canada show the largest relative drops (from -34% to -24%). The largest absolute reductions were found for Canada and the EU (-0.8 t/ha). These yield losses translate into proportional production cutbacks the most marked of which correspond to the EU (-22 Mt), Russia (-17 Mt), China (-15 Mt), and Australia (-8 Mt). Domestic markets clear at higher prices across scenarios, especially in the EU, Kazakhstan, and Russia (15%-17%). Positive cross-price effects lead to higher prices in the case of low-protein feed substitutes (e.g., other grains, cereal brans, dried beet pulp, molasses) but also for medium-protein meals (e.g., corn gluten, dried distiller's grains, field peas, whey powder). As a result, the average price of all protein feed rises by up to 8% (Kazakhstan).

<< Figure 3 about here >>

The potential impacts of negative extremes are more pronounced on trade. With respect to the baseline, exports from Russia and the EU decrease significantly (-12 Mt in each scenario), followed by Australia (-8 Mt), Canada (-6 Mt), and Kazakhstan (-5 Mt). Export volumes from the remaining key players drop by less than 4 Mt. In order for total domestic demand to be met in China, adverse growing conditions in the latter lead imports to roughly triple (+5 Mt), thus remarkably reducing self-sufficiency and increasing import dependency. [8,9] EU ad-valorem tariffs currently levied on imported grains (e.g., maize, rye, cereal brans) decrease from 7% to 5% in order for domestic (feed) demand to be met mainly with non-wheat imports. The culmination of lower global availability of wheat leads 2018/19 international prices to rise across scenarios, most pronouncedly in the EU (11%; +24 USD/t), Russian (8%; +17 USD/t), and Australian (5%; +10 USD/t) cases.[10]

On the other hand, favorable agroclimatic extremes (green bar portions) boost wheat yields. Large absolute increases relative to the baseline were found for Australia and Ukraine (+0.9 t/ha), Kazakhstan and China (+0.8 t/ha), and Canada and the EU (+0.6 t/ha). Salient production expansions can be noted for China (+19 Mt), the EU (+17 Mt), Russia (+12 Mt), Australia (+11 Mt), and Kazakhstan (+10 Mt). Producer prices fall the most in Kazakhstan (-15%) and China (-12%), in the remaining cases ranging between -10% (EU) and -2% (USA). Low-protein feed use increases across scenarios, while average feed prices drop by up to -8% (Kazakhstan). Consumer prices follow in China (-9%) and Kazakhstan (-5%). Wheat exports over-double from Kazakhstan (+10 Mt), increase by about half in Australia (+11 Mt), one-third in the EU (+11 Mt), Russia (+9 Mt), and Ukraine (+6 Mt), and by about 4 Mt in Canada. China displays a near-zero trade balance. Improved trade balances lead to higher global wheat availability throughout, thus reducing international prices by 7% (EU case), 5% (Russia, Australia, Kazakhstan), or less.

4.2 Domestic maize markets

Figure 4 depicts potential market effects from unfavorable agroclimatic extremes in key maize regions. Vast yield reductions can be detected for the USA (-2.5 t/ha), South Africa (-1.9 t/ha), and Russia (-1.6 t/ha). Sizeable production losses occur in the US (-84 Mt), China (-18 Mt), the EU (-15 Mt), and Brazil (-11 Mt). Producer prices build up the most in the USA (54%; +76 USD/t) and South Africa (24%; +502 rand/t). Average protein feed prices rise by up to 2%. Consumer prices increase the most in China (16%) and South Africa (5%).

Exports decrease substantially with respect to the baseline, especially from the US (-39 Mt), Brazil (-9 Mt), Russia (-5 Mt), and Argentina (-4 Mt). Maize imports double in the EU (+13 Mt) and China (+1.5 Mt), while they rise about threefold in South Africa (+3 Mt). Ad-valorem import tariffs are lifted in the EU (maize) and slightly drop in the USA (non-main grains, from 30% to 27%). South Africa becomes temporarily a net importer with a record-low self-sufficiency ratio (70) and a record-high import-dependency ratio (35), with a recovery phase of one year. The strongest price transmission on the world market comes from the USA (44%; +73 USD/t), which makes up the lion's market share in global exports.[11] World price effects from other regions are notably lower (e.g., 8% in the EU case and 6% in the Brazilian case).

<< Figure 4 about here >>

Favorable extremes reverse the yield picture particularly in South Africa (+1.7 t/ha), the USA (+1.4 t/ha), and Ukraine (+1.3 t/ha). In some cases, boosted yields lead to record production. For example, simulated US maize yields of 12.2 t/ha (previous record: 11 t/ha) lead to the production of 416 Mt (+31 Mt over the historical maximum from 2016/17). Similarly, Brazilian and Argentinian production climb to 94 Mt and 45 Mt against historical records of 81 Mt and 34 Mt, respectively. Producer prices drop the most in EU (-27%; -43 EUR/t), South Africa (-24%; -518 rand/t), and the USA (-17%; -24 USD/t), with smaller drops observed for China (-12%; -256 CNY/t), Brazil (-8%; -42 BRL/t), and Argentina (-4%; -129 ARS/t). Average protein feed prices drop notably in the USA (-11%), the EU (-11%), and China (-6%), while low-protein feed gains importance throughout. Consumer prices fall mostly in China (-11%) and South Africa (-5%). Exports expand from the USA (+19 Mt), Brazil and South Africa (+9 Mt), Ukraine (+5 Mt), and Argentina (+4 Mt). EU imports drop by 80% (-13 Mt), while ad-valorem tariffs for maize roughly double. The international price of maize falls notably due in the US shock (-16%; -26 USD/t), but also in the EU (-13 USD/t), Brazilian, and South African cases (-9 USD/t).

5 Concluding remarks

Agroclimatic extremes constitute a substantially under-researched area both in terms of types of attribution, likelihood, magnitude of impacts, and crops and regions covered, let alone bringing these aspects together in the form of integrated assessment. In this paper, we contributed to the empirical literature by incorporating a non-parametric, crop- and region-specific, composite yield stress index into a partial equilibrium model of global agriculture. By re-enforcing extreme post-planting agroclimatic conditions of the past into the near future, we simulated the potential short-to-medium term impacts on key domestic and international agricultural commodity markets.

The response of crop prices to agroclimatic extremes is in conceptual accordance with expectations: extremely unfavorable (favorable) growing conditions lead crop prices to clear above (under) the baseline, which typically assumes 'normal' agroclimate but without modeling it. At the domestic level, the magnitude of the price response differs per crop-country combination and depends mainly on the local sensitivity of food systems to extremes (i.e., on the yield impact coefficients) and the market status-quo at the time of the shock, and to a lesser extent on the size of the shocks, which are relatively comparable across regions. At the international level, the price transmission is visible in all cases with the usual suspects (i.e., key producers, exporters, and importers) being responsible for the most pronounced effects. Significant trade impacts were found in either direction indicating both winners and losers depending on the scenario. Developed countries may lose or gain market shares, while developing economies may face temporary self-sufficiency issues and changes in the trade position. Transmission to global markets is more pronounced in big exporters but the effect is visible also when big importers are shocked (China, EU maize).

A particularly interesting finding is that although yields display symmetry to the direction of the agroclimatic shock, the endogenously transmitted effect on commodity prices is consistently asymmetric. Domestic and world prices appear to be more responsive to negative agrometeorological anomalies shocks rather than to favorable ones, and this holds irrespective of the crop and trade position of the affected country. For example, a 1% wheat price increase in Australia comes from a 3.6% yield drop due to unfavorable agroclimate, whereas a 1% price decrease is the result of a 5% yield increase due to favorable agroclimate. Equivalently, a 1% drop in EU maize yields increases the corresponding world price by 0.33%, whereas a 1% yield increase reduces the world price by a smaller amount, 0.2%. The likely explanation for this model result is the level of beginning world stocks. Abundant grain supplies over the last five years have led to high world inventories that exert downward pressure on international prices (OECD/FAO 2017, European Commission 2017). This pressure renders the magnitude of price explosion due to grand-scale harvest failures greater than further pressure due to continuing overproduction. Persistent negative extremes may deplete grain stocks and thus render prices more responsive in the future. For such cases, strategic global responses may worth setting out within the World Trade Organization's reform programs.

In interpreting our results four important remarks ought to be made. First, the most extreme agroclimatic anomalies of the recent past were taken as normative values for the simulation experiment. The recent development of the CSI renders the estimation of the likelihood of the examined scenarios not straightforward. Ongoing work on probabilistic projection of extreme events will soon enable us to quantify the risk (magnitude × probability) of such events (Janetos et al. 2017). In essence, one would expect regions already experiencing high yields to be subject to larger yield reductions, and regions experiencing low yields being subject to larger yield improvements. Second, only two crops were examined herein. We leave soybean and rice for future work. Furthermore, the correlation of extreme events across crops in the same or different countries merits further examination (e.g., different time windows, prone to different types of extremes). Third, only single-year events were examined. The impacts of such events are moderated by a return to average conditions next year and, by definition, the absence of simultaneous extremes in other countries. With an increased frequency of extreme events, there is the possibility of concurrent extremes in a single year and recurrent extremes in the following years. Globally concurrent shocks can generally compensate or ameliorate international market impacts, with the combined price transmission assumed to be nonlinear and multiplicative. Fourth, record-high production volumes are marked in a number of cases. By construction, domestic production changes are lower than the historical ones but difficult to validate without a biophysical model. Finally, Aglink-Cosimo does not distinguish between rainfed and irrigated farming. Neither can changes on the input side be inferred. This may not pose a significant problem for short-to-medium term projections. But for long-term ones if the adaptive capacity of each region changes (e.g., through irrigation or cultivars that higher tolerance to extremes), this has to be considered. Overall, little can be said about the degree of future exposure and vulnerability of the examined regions to extremes, which may be shaped by evolving adaptation potential in the form of, say, early warning systems or changing water availability and more efficient use. Despite these limitations, factoring composite indices into a large-scale economic model has allowed us to provide the short-term global picture from regional extremes, paving the way for more advanced analyses to be conducted in the future.

Moving beyond the implementation of deterministic scenarios, a promising avenue is the consideration of uncertainty in the attributes of extreme events. In order to understand the potential paths of commodity markets due to random agroclimatic anomalies, we are currently developing a stochastic framework that takes into account data, parameter, and macroeconomic uncertainty. Data uncertainty refers to the derivation of CSI values that reflect globally concurrent and successive anomalies up to the year 2030. Parameter uncertainty pertains to potentially non-constant sensitivity of crop yields to regional extremes (e.g., stochastic impact coefficients based on their sampling distributions, as in in figure 2). Finally, these types of uncertainty should be examined conjunctly with macroeconomic factors (e.g., oil prices, exchange rates) that affect production costs and trade to a large extent.

In this paper we highlighted the importance of extreme events that could affect multiple domestic agricultural markets, followed in many cases by significant transmission to international markets within the same annual cycle. Data needs are large, and knowledge gaps are still significant. The use of Integrated Assessment Models and economic model intercomparison (e.g., Nelson et al. 2014) with explicit consideration of climate extremes is the next step. After having provided the magnitude of possible economic impacts, the quantification of likelihood and the investigation of policy mechanisms to ameliorate extreme consequences from systemic risks have to be examined.

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Table 1: Shares (%) in Total Global Production and Exports, 2012-2016

Wheat			Maize		
Region	QP	EX	Region	QP	EX
EU-28	21	19	**USA**	35	35
China^{M}	18	0	**China**	22	0
India^{M}	13	2	**Brazil**	8	20
USA^{M}	8	17	**EU-28**^{M}	7	2
Russian Fed.	8	12	**Argentina**	3	13
Canada	4	14	**Ukraine**	3	14
Australia	4	12	*India*	2	2
Pakistan	4	0	*Mexico*^{M}	2	1
Ukraine	3	8	*Canada*	1	1
Turkey^{M}	3	2	**Russian Fed.**	1	3
Kazakhstan	2	5	**South Africa**	1	1
Argentina	2	4	*EUE*	1	1
Sum	*90*	*95*	*Sum*	*86*	*93*

Note: ‘QP’ – production, ‘EX’ – exports, 'M' – major importer. Regions sorted by production shares. Regions in bold (italics) are examined herein (ongoing work).

Source: Own calculation based on OECD/FAO (2017).

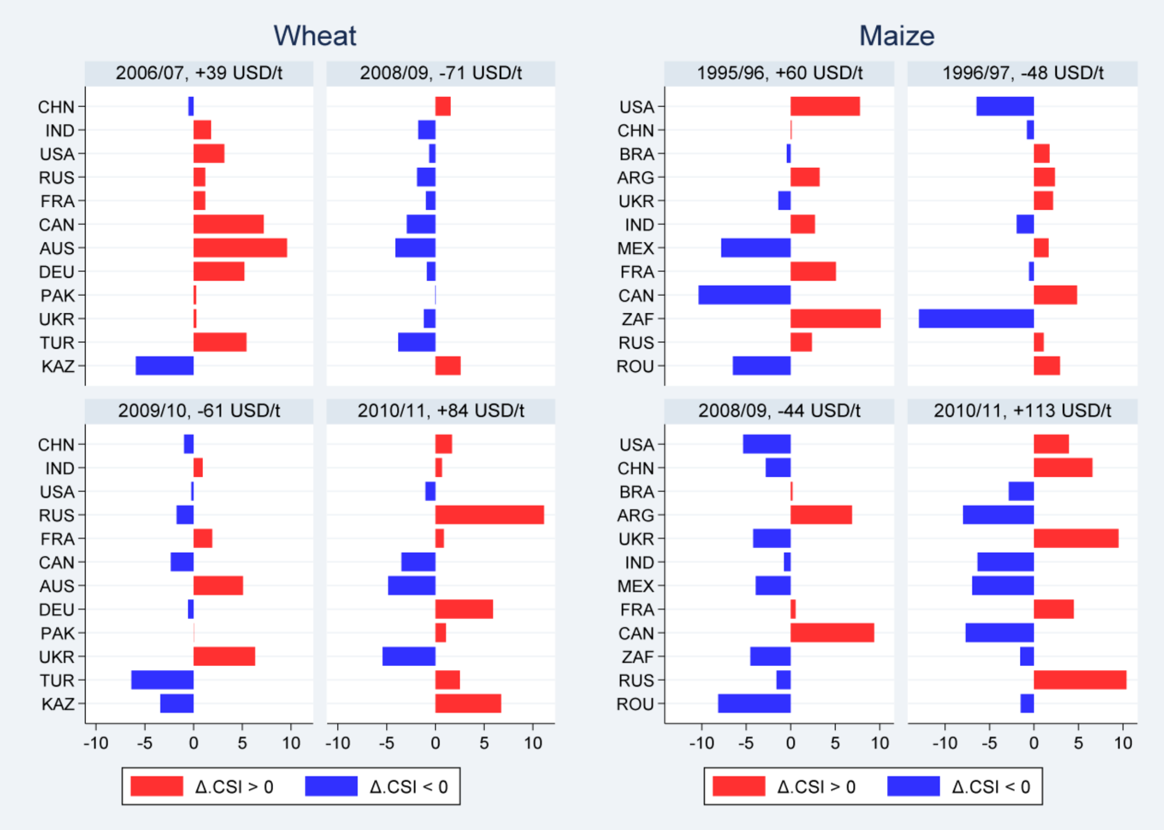

Figure 1: Concurrent agroclimatic variability in selected regions and international crop prices

Note: Red (blue) denotes an absolute increase (decrease) in the value of the corresponding Combined Stress Index and thus deterioration (improvement) in post-planting growing conditions compared to the previous year. World price changes on labels (No. 2, hard red winter wheat, US FOB, Gulf; No. 2, yellow maize, US FOB, Gulf). Regions sorted by production shares (2012-2016). Nomenclature: ISO 3166-1 alpha-3.

Source: Own elaboration based on OECD/FAO (2017).

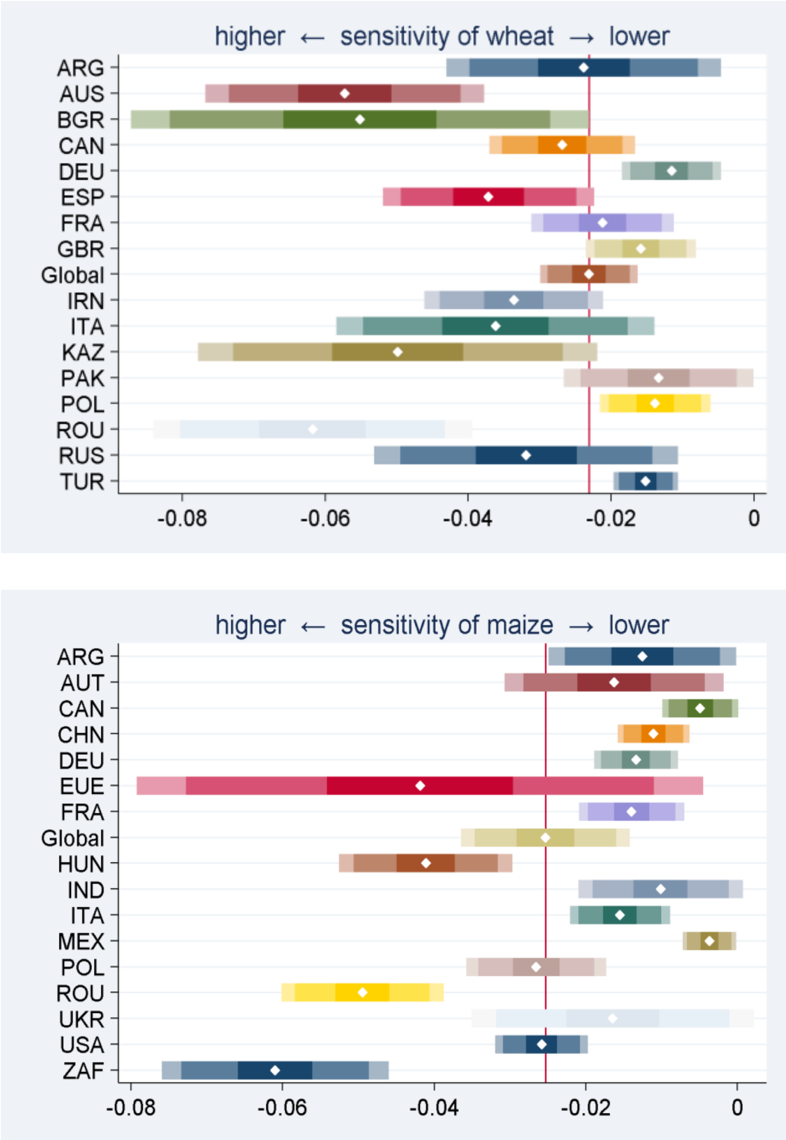

Figure 2: Sensitivity of crop yields to agroclimatic extremes in selected countries, 1980-2010

Note: Coefficients (white dots within bars) show the average response of regional yields (t/ha, logged) to a marginal increase in the value of the corresponding Combined Stress Index ($p < 0.05$). Bar shades represent confidence intervals based on the sampling distributions of the estimates (dark – 50%; medium – 90%; light – 95%). Red lines show the global mean response based on pooled models. Nomenclature: ISO 3166-1 alpha-3 (EUE – Eastern Europe).

Source: Own estimation based on OECD/FAO (2017) and Eurostat (2017).

Figure 3: Simulated agroclimatic extremes and selected wheat markets, 2018/19

Note: The bars show % deviation from the baseline under single region-crop-year scenarios. QP – production, QC – consumption (all uses), EX – exports, IM – imports, ST – ending stocks, PP – producer price, WP – world price. Baseline projections are shown in annex tables A1 and A2.

Source: Own estimation based on European Commission (2017).

Figure 4: Simulated agroclimatic extremes and selected maize markets, 2018/19

Note: The bars show % deviation from the baseline under single region-crop-year scenarios. QP – production, QC – consumption (all uses), EX – exports, IM – imports, ST – ending stocks, PP – producer price, WP – world price. Baseline projections are shown in annex tables A1 and A2.

Source: Own estimation based on European Commission (2017).

ANNEX

Table A1: Baseline Projections for Selected Markets, 2018/19

Region	YLD	QP	QC	EX	IM	ST	PP
Wheat							
EU-28	5.80	155,410	128,015	31,444	5,093	13,945	171
China	5.31	127,878	128,495	211	2,710	84,523	2,075
Russian Fed.	2.49	66,691	42,202	26,649	851	11,571	7,457
USA	3.20	53,821	32,755	26,555	3,408	26,631	168
Canada	3.26	30,278	8,961	21,446	96	6,069	167
Australia	2.20	28,900	9,214	19,666	20	5,840	276
Ukraine	3.92	27,058	11,226	15,633	50	2,935	4,908
Kazakhstan	1.25	15,278	7,274	7,902	101	2,662	63,144
Maize							
USA	10.83	367,016	325,527	48,376	1,385	53,253	141
China	5.96	215,565	224,212	5	1,548	82,655	2,198
Brazil	5.40	82,901	55,814	26,862	653	6,708	507
EU-28	7.14	63,948	72,828	2,746	13,053	16,693	160
Argentina	7.45	40,464	18,963	21,542	0	3,369	3,115
Ukraine	6.79	28,742	8,774	19,581	25	3,963	3,901
Russian Fed.	4.78	14,353	9,225	5,285	101	923	9,444
South Africa	5.11	13,222	12,149	2,292	1,112	1,256	2,118

Note: YLD – yield (t/ha), QP – production (kt), QC – consumption (all uses; kt), EX – exports (kt), IM – imports (kt), ST – ending stocks (kt), PP – producer price (domestic currency/t).

Source: Own estimation based on European Commission (2017).

Table A2: Baseline International Prices, 2018/19

Crop	International price, USD/t	Reference
Wheat	206.8	No. 2, hard red winter, US FOB, Gulf
Maize	164.3	No. 2, yellow, US FOB, Gulf

Source: Own estimation based on European Commission (2017).

[1] If an alternative index that captures extremes during planting had been used instead, the derivation of impact coefficients based on a direct regression of yields against that index, or an explicit treatment of the area effect, would have been preferable for use in Aglink-Cosimo.

[2] Regional aggregate for Eastern Europe.

[3] The global impact coefficients for wheat and maize equal -0.0231 ($p < 0.001$, $n = 723$ yield-CSI pairs from 25 countries/regions) and -0.0253 ($p < 0.001$, $n = 614$ yield-CSI pairs from 22 countries/regions), respectively. The pooled models were estimated by regressing first-differenced yields on their first-differenced CSIs (feasible GLS, robust VCE).

[4] *(production) - (consumption) + (imports) - (exports) + (beginning stocks) - (carryout) = 0*

[5] The CSI was designed to have a linear relationship with yields. Therefore, some of the impact coefficients were adjusted (up to ±2 standard errors of Eq.(1.1)) to render yields more elastic or inelastic to extremes depending on the level of the baseline yield. This adjustment *(i)* copes with non-linearity between climatic variables and yields that exists (see Quiggin and Horowitz 2003) but cannot be uncovered with the current design of the CSI, and *(ii)* avoids an extremely big jump (big drop) of already high (already low) baseline yields, while allowing for the opposite (i.e., a big jump when yields are low, and a big drop when yields are high).

[6] December 2017 release (European Commission 2017).

[7] The extent to which extreme conditions for one crop coincide with extreme conditions for another merits further investigation. In general, wheat and maize have different biophysical thresholds and are most prone to extremes in different time windows during the growing season. We leave concurrent and recurrent events for future work.

[8] *Self-sufficiency ratio = 100 × production / (production + imports – exports)*

[9] *Import-dependency ratio = 100 × imports / (production + imports – exports)*

[10] No. 2, hard red winter wheat, US FOB, Gulf (June/May).

[11] No. 2, yellow maize, US FOB, Gulf (September/August).