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Extreme Weather and Global Agricultural Markets: Experimental Analysis of the Impacts of Heat Waves on Wheat Markets

Thomas Chatzopoulos*, Ignacio Pèrez Domínguez, Matteo Zampieri, Andrea Toreti

European Commission, Joint Research Centre, Sustainable Resources Directorate
**corresponding author: thomas.chatzopoulos@ec.europa.eu*

ABSTRACT

Extreme-weather events frequently drive production fluctuations, price volatility, and hence uncertainty on agricultural commodity markets. Simulation models of global agriculture typically assume normal weather in deterministic scenarios, contain no explicit parameterization of weather elements on the supply side, and confound multitudinous sources of yield fluctuation in exogenous yield shocks. As a part of a wider project on extreme events modelling, in this paper we present the experimental design of a first attempt to explicitly parameterize extreme weather into a partial equilibrium model of global agriculture (Aglink-Cosimo). We outline the main model additions and present preliminary estimates of wheat yield-to-heat elasticities for key regions. We also present the potential wheat market impacts from a counterfactual heat-wave scenario in Australia. Finally, we outline ongoing and future work on multi-scenario analysis in the context of extreme weather and global markets.

1. Introduction

Over the last two decades we have witnessed a deluge of extreme weather events of unprecedented frequencies, intensities, duration, and spatial coverage (IPCC 2012, WMO 2013, Zampieri et al. 2016). The latest IPCC report leaves little room for doubt on high-temperature extremes in particular, which will very likely occur more frequently and last longer (IPCC 2012: 13). Given the high sensitivity of the agricultural sector to extreme weather events and the induced production fluctuations and price volatility, this paper focuses on agricultural commodity market modelling.

Extreme weather events affect commodity markets through a two-fold impact on crop production. The direct effect is biophysical and pertains to yield reduction when crops are hit by extreme weather at critical developmental stages. The indirect effect boils down to altering the efficiency -and perhaps the timing- of input application. This two-fold impact dictates fluctuations in production and stock-to-use ratios as well as price volatility at least in the short run. As the 2007/08 and 2010/11 food crises have shown, aggressive trade policy responses to mitigate weather-induced high prices may also occur (Trostle 2008, Mittal 2009, Willenbockel 2012). Not surpisingly, inferred impacts of extreme weather events on market fundamentals are concurrently mentioned by policy makers, market analysts, and the media; paradoxically enough, they have remained a subject considerably less-honoured than climate change from a quantitative viewpoint. What could the possible impacts of another European heat wave be on domestic crop production, commodity prices,

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and trade with the rest of the world? How long would it take for key markets to recover after single or recurrent weather shocks? How do market effects transmit to other countries? Would international agreements, stock management, or other possible trade responses to extreme weather stabilize high commodity prices? What are the global market implications? Within a broader project on extreme events modelling (C^2ESAM)[1], we attempt to cast light on the above questions.

The main analytical tool to be used is a recursive-dynamic partial equilibrium (PE) model for global agricultural commodity markets, Aglink-Cosimo (*www.agri-outlook.org*). Our main distinction from previous studies that deal with climate- or weather-related issues is that we are the first to attempt an explicit parameterization of extreme weather into behavioural equations on the supply side of a multi-commodity model. This comprises the following steps:

i. an extension of existing crop-yield equations for key non-EU regions with heat-wave indices as explanatory variables;
ii. the development of reduced-form crop-yield equations for key EU member states (MS) with heat-wave indices as explanatory variables (partial disaggregation), and the transmission of weather impacts from the MS level to the EU level (cross-level linkage);
iii. the econometric estimation of the partial effects of heat waves on wheat yields (yield-to-heat elasticities) for non-EU and EU countries, as well as yield-transmission (cross-level) elasticities from MS to the EU level;
iv. model enhancement and alternative ("with-weather") baseline calibration;
v. a general framework for multi-scenario simulation in the context of extreme weather events.

This paper focuses on points *(i)-(iii)* with only a brief treatment of points *(iv)* and *(v)*, and is organized as follows. Section 2 gives a brief non-technical overview of the current version of the producer core system in Aglink-Cosimo. Section 3 presents the proposed extensions and preliminary wheat yield-to-heat elasticities for key global producers. In Section 4 the potential wheat market impacts of a counterfactual heat wave in Australia are presented, and the concept of a deterministic multi-scenario analysis that we intend to implement in the future is outlined. Section 5 concludes with challenges and upcoming work.

2. Brief description of relevant equations

Aglink-Cosimo includes annual supply, demand, price, and trade simulations for 40 agricultural commodities and 44 regions in a 10-year horizon (Araujo-Enciso et al. 2015a). The model is elasticity-driven and consists of commodity market balances including supply, demand, trade, and stocks, with linearized behavioural equations that are solved as a square system, and prices allowing for market closure. Aglink-Cosimo is developed and maintained by the OECD and the FAO Secretariats with a defined group of users from national administrations and research institutes. The European Commission uses a modified version of the model to annually generate baseline projections for counterfactual policy analysis at the EU level[2].

In Aglink-Cosimo, crop production (*QP*) is obtained by multiplying average regional yield (*YLD*) by the harvested area (*AH*):

$$QP_{c,r,t} = YLD_{c,r,t} * AH_{c,r,t} \quad (1)$$

where *c*, *r*, and *t* are the crop, region, and market-year identifiers respectively. Crop yield is generally modelled endogenously as a function of a first-order trend (*T*) in levels and a logged "price margin" (*PM*), the latter being dependent on lagged producer prices (*PP*) and policy variables (*EP*), all deflated by a composite index of production costs (*CPCI*):

$$lnYLD_{c,r,t} = a_{c,r} + b_1 * T + b_2 * lnPM_{c,r,t-1} + lnR_{c,r,t} \quad (2)$$

[1] Concurrent Climate Extremes and Shocks on Agricultural Markets
[2] For details, see *https://ec.europa.eu/agriculture/markets-and-prices/medium-term-outlook_en*.

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where

$$lnPM_{c,r,t-1} = ln\{ (PP_{c,r,t-1} + EP_{c,r,t-1}) / (b_4*CPCI_{c,r,t-1} + (1 - b_4)*CPCI_{c,r,t}) \} \quad (3)$$

The *b*'s in In Eqs. (2) and (3) are exogenously determined coefficients (e.g., b_2 is a yield-to-price elasticity). The trend is a proxy for technological change and typically assumed to have a positive effect on yields over time. The cost index is endogenous and makes up for the absence of an explicit cost function. The terms *a* (constant) and *R* ("*R*-factors") are interdependent calibration parameters: the constant is re-estimated during the baseline development to produce logged *R*-factors with a mean of 1. Therefore, *a* and the *R*-factors can be thought of as "garbage bins" for time-invariant and time-varying factors respectively that are missing from Eq. (2). The *R*-factors are endogenous during model calibration and exogenous in scenario simulation.

In the EU, harvested area (*AH*) is modelled within a system of equations that consider the relative competitiveness of each crop with respect to soft wheat, total area harvested for crops (AH_{crops}), and arable set-aside fallow land (AH_{set}):

$$AH_{c,r,t} = AH..SHR_{c,r,t}*(AH_{crops,r,t} - AH_{set,r,t}) \quad (4)$$

with

$$AH..SHR_{c,r,t} = f\ (RH,\ EP,\ CPCI\ of\ crop\ c\ relative\ to\ soft\ wheat) \quad (5)$$

$$AH_{crops,r,t} = AH_{UAA,r,t} - AH_{pasture,r,t} - AH_{other,r,t} \quad (6)$$

$$AH_{set,r,t} = f\ (AH_{crops,r,t},\ RH,\ EP,\ additional\ policy\text{-}driven\ set\text{-}aside) \quad (7)$$

Crop returns per hectare (*RH*) are modelled as weighted three-year moving averages to filter out strong yield and price fluctuations:

$$RH_{c,r,t} = 0.5(PP*YLD)_{c,r,t} + 0.3(PP*YLD)_{c,r,t-1} + 0.2(PP*YLD)_{c,r,t-2} \quad (8)$$

3. Extensions

3.1 Yield shocks vs. weather shocks

In economic modelling studies, the impacts of climate change or extreme weather events are typically simulated with instantaneous supply-side shocks (e.g., Willenbockel 2012, Araujo-Enciso et al. 2015b, Wiebe et al. 2015). This is accomplished with the introduction of % yield changes per *c*, *r* and *t*, and a subsequent comparison of the model solution(s) from the simulated scenario(s) over the counterfactual baseline projections. This approach is based on historical yield trends, deviations, expert judgements, and is straightforward to implement.

In this paper we take a different and more structural approach: we explicitly parameterize extreme weather into the supply-equation system of Aglink-Cosimo. This will enables us to perform direct shocks on weather instead of yields. For example, upon adding an exogenous extreme-weather index, *XWI*, as an explanatory variable into the yield equation (Eq. 2), we obtain the following equation:

$$lnYLD_{c,r,t} = a_{c,r} + b_1*T + b_2*lnPM_{c,r,t-1} + b_3*XWI_{c,r,t} + lnR_{c,r,t} \quad (9)$$

where b_3 is the partial effect of *XWI* on the yield[3] of crop *c* at region *r*. This mechanism dictates direct and indirect extreme-weather effects on other items: a direct effect on wheat yield (Eq. 9), an indirect but proportionate effect on production (Eq. 9 → Eq. 1), an indirect effect on wheat returns (Eq. 9 → Eq. 8), an

[3] Given that *YLD* is logged and *XWI* is measured in levels, 100*b_3 is essentially a semi-elasticity.

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indirect and lagged effect on area allocation[4] (Eq. 9 → Eq. 8 → Eq. 5 → Eq. 4), and an indirect effect on domestic market price clearance[5].

The explicit parameterization of extreme weather into the model followed by direct shocks on the weather variables has a number of advantages over the traditional way of performing shocks on yields. First, the direct and indirect impacts of specific events on all three dimensions (*c, r, t*) of the relevant behavioural equations can be simulated. In the traditional approach, neither is it clear which part of the induced yield shock comes from extreme weather (it is confounded with diseases, pests, and other omitted factors that vary randomly) nor what type of extreme weather event is actually producing the yield anomaly. Second, in our approach the impact of extreme weather is driven by region- , commodity-, and index-specific elasticities that are econometrically estimated based on historical aggregated data, as opposed to user-defined changes in yields or to results from disaggregated process-based models. Third, the specification of existing behavioural equations in Aglink is improved both conceptually and statistically; conceptually because the yield equations now include an extreme-weather driver in addition to the economic driver, and statistically because the explanatory power of the yield equations is in most cases improved (see Tables 1 and 2). Fourth, projected values of future extreme weather events could be used as direct input into the model. Finally, we also expect an improvement in model calibration and the partial stochastics module[6]. Scaling the *R*-factors on 1 will likely be more efficient because a previously omitted time-varying significant determinant of yield downturns is now explicitly into the model.

3.2 Which crop and regions?

In this paper we focus on wheat, a leading source of vegetable protein in human food consumption. Wheat is grown on more land area than any other commercial food, and world trade in wheat is greater than for all other crops together (JRC 2016). Therefore, we expect the effects of extreme weather to be visible on market fundamentals. We plan to also examine maize, rice, and soybeans in the future.

For the analysis we focus on the 12 key producers that account for the lion's share of global wheat production (about 90% p.a. in the last five years): EU-28^{X,M}, China^{M}, India^{M}, USA^{X,M}, Russia^{X}, Canada^{X}, Australia^{X}, Pakistan, Turkey^{M}, Ukraine^{X}, Argentina^{X}, and Kazakhstan^{X}. Superscripts denote key exporters (X) and importers (M).

3.3 Which extreme-weather index?

Extreme events are often characterized, and therefore diagnosed, as the exceedance of specific thresholds by relevant climatic variables. By definition, we are concerned with sudden weather changes and *not* gradual climate change, which would require a different modelling treatment.

Relevant extremes affecting wheat yield are periods of exceptionally warm temperatures (i.e., heat wave), periods of exceptionally low precipitation (drought), severe winter/spring frosts, and extremely wet/cool conditions that enhance plant diseases (e.g., Lesk et al. 2016). We started our analysis with heat waves because they are, arguably, the most relevant extreme affecting wheat yield (Lesk et al. 2016).

We use two heat-wave indices that are defined as the total number of consecutive days exceeding a maximum temperature threshold during the last three months before harvest. The temperature threshold is exogenously determined in the parametric index (*HWI*) and endogenously determined in the non-parametric index

[4] A weather shock at *t* is assumed to hit farmers by surprise after planting decisions have been executed. Therefore, a weather event at *t* does not change harvested area -which equals planted area in Aglink- and land allocation across crops at *t*, but it is allowed to indirectly affect it at *t+1*.

[5] (production) – (consumption) + (imports) – (exports) + (lagged stocks) – (current stocks) = 0. For details, see Araujo-Enciso et al. (2015a) or OECD-FAO (2015).

[6] In addition to the deterministic model version, Aglink has a partial stochastics module that takes into account broad historical yield variability of unspecified origin (Burrell and Nii-Naate 2013).

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(*HWMId;* Zampieri et al. 2016). The results regarding the parametric index presented in this paper draw on a 34-degree-celsius threshold[7]. The *HWMId* takes also into account the amplitude of temperature anomalies.

The attractiveness of composite indices, opposed to unidimensional indices, is that multiple weather attributes can be accounted for at once. Our heat-wave indices, for instance, account for:

- ***occurrence***: the indices take on a positive value if a heat wave occurs, and a zero value if it doesn't;
- ***temporal duration***: the indices are frequency counts;
- ***intensity***: the indices measure *consecutive* days; *HWMId* further accounts for the amplitude of temperature anomalies exceeding the threshold;
- ***spatial coverage****:* only wheat-growing areas are considered, per region;
- ***timing****:* the indices are computed for the last three months before the average harvest of wheat, thus covering at least anthesis and grain-filling, which are the phenological stages during which optimal temperatures for wheat development are higher than in earlier growth phases (see Porter and Gawith 1998).

It is important to note that although the heat indices can be computed separately for winter and spring wheat, this distinction is not made in the standard Aglink-Cosimo modelling system. The decision of which type of wheat is more relevant depends on our a priori knowledge of the relative importance of the corresponding agro-managements practices in determining total production[8].

3.4 Treatment of non-EU regions

The procedure of incorporating extreme weather into the wheat yield equations of non-EU regions is relatively straightforward. The standard wheat yield equations (Eq. 2) in Aglink-Cosimo were econometrically re-estimated with one extreme-weather index at a time as an additional explanatory variable (Eq. 9). Preliminary estimates of the corresponding partial effects for key regions are displayed in Table 1. For instance, we see that if the *HWI* value in Canada increases by one unit (i.e., if the number of consecutive days where temperature in wheat-growing regions exceeds 34 degrees from April to July), the expected national yield of wheat decreases by 5.2%.

[7] Lethal temperatures for various processes and phonological phases in wheat cultivation are reviewed in Porter and Gawith (1999) and Luo (2011).

[8] In most regions the temporal difference between the average harvesting dates of spring and winter wheat is less than three months, which implies that the corresponding weather-index captures heat waves before the harvest of both types of wheat.

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Table 1: Yield-to-heat partial effects: preliminary time-series (OLS) estimates for key wheat producers

Region	*HWI*	*HWMId*	R^2 (ΔR^2)	*HW timing*
USA		-0.011	0.62 (+7%)	4.0 – 7.0
RUS	-0.050		0.60 (+21%)	5.6 – 8.6
CAN	-0.052		0.66 (+16%)	5.0 – 8.0
AUS	-0.109		0.46 (+38%)	8.0 – 11.0
ARG	-0.025		0.64 (+8%)	8.9 – 11.9
KAZ	-0.093		0.53 (+43%)	3.9 – 6.9

Note: The dependent variable is the mean national yield of wheat (t/ha, logarithmized). Intercepts, trend and price coefficients (see Section 2) are omitted from the Table to keep the focus on *HWI*, which is described in Section 3.3. ΔR^2 is the improvement in the explanatory power of the standard Aglink equations upon including heat-wave indices as predictors. The column *'HW timing'* shows the three-month windows over which the *HW* indices were computed (1 = January). Time-series samples: n_{max} = 31 years (1981-2010), n_{min} = 20 years (1991-2010, for KAZ). Estimates are significant at least at the 0.05 level (homoskedastic VCE).

Source: Own estimation based on JRC (2016) and Zampieri et al. (2016).

3.5 Treatment of the EU market

The EU (E15 + NMS) is treated as a single market in Aglink but none of our weather indices appear to be statistically significant determinants of EU-level yields due to the aggregation of 28 countries into a single region, which masks heterogeneous local climate and weather variation. Therefore, we partially disaggregate the E15 and NMS wheat yield equations to MS-level equations[9], from which extreme-weather impacts are endogenously transmitted to E15 and NMS. In addition to that, since the EU yield equations further differentiate between soft wheat (WTS) and durum wheat (WTD), so do the newly generated MS-level equations.

We follow a top-down approach. First, we identify those MS where wheat yield variations are jointly significant determinants of the EU-level wheat yield variation. This leads to the re-estimation of the following Aglink equations with various combinations of MS-level yields as additional explanatory variables:

$$lnYLD_{WTS,E15,t} = a_{WTS,E15} + b_1*T + b_2*lnPM_{WTS,E15,t-1} + b_i*lnYLD_{ms,t} + lnR_{WTS,E15,t} \quad (10)$$

$$lnYLD_{WTD,E15,t} = a_{WTD,E15} + b_1*T + b_2*lnPM_{WTD,E15,t-1} + b_i*lnYLD_{ms,t} + lnR_{WTD,E15,t} \quad (11)$$

$$lnYLD_{WTS,NMS,t} = a_{WTS,NMS} + b_1*T + b_2*lnPM_{WTS,NMS,t-1} + b_j*lnYLD_{ms,t} + lnR_{WTS,NMS,t} \quad (12)$$

$$lnYLD_{WTD,NMS,t} = a_{WTD,NMS} + b_1*T + b_2*lnPM_{WTD,NMS,t-1} + b_j*lnYLD_{ms,t} + lnR_{WTD,NMS,t} \quad (13)$$

where b_i and b_j are wheat-specific "cross-level" yield elasticities for the ith (E15) or j^{th} (NMS) member state respectively. These elasticities reflect an MS-to-EU yield transmission effect that will then be linked to MS-level equations that model $lnYLD_{ms,t}$ as a function of extreme weather. This data-driven approach is based on econometric estimation of elasticities instead of calculation of user-defined weights. Upon testing various combinations of MS into the above equations through stepwise deletion, we arrived at the conclusion that the following MS-level yields are historically and jointly the best determinants of EU-level yields:

- Soft wheat in E15: France, Germany, United Kingdom, Spain
- Durum wheat in E15: Italy, Spain
- Soft wheat in NMS: Poland, Romania, Hungary
- Durum wheat in NMS: Hungary

[9] It is a partial disaggregation because prices clear at the EU level.

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On average, about 86% of the total EU wheat production comes from these countries. Figure 1 shows, for instance, that soft wheat yield variation in E15 is indeed driven by yield variation in the aforementioned four MS.

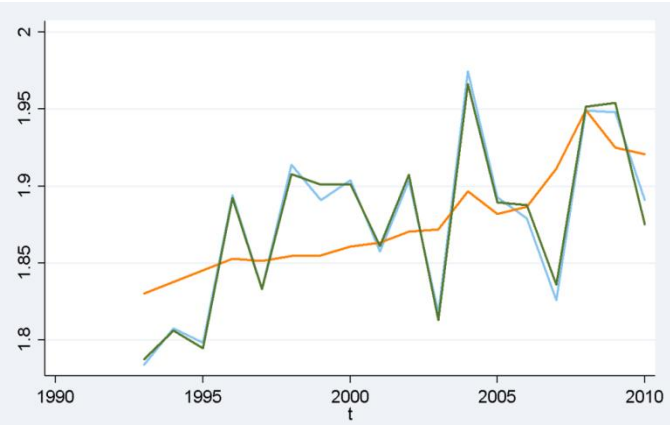

Figure 1: Soft wheat yields in E15: observed (blue) vs. Aglink-predicted (orange) vs. Aglink plus MS-level yields as predictors (green)

Indicatively, the explanatory power of the current Aglink equation for WTS in E15 improves dramatically from 9% (no MS-level yields as predictors) to 95%. Table 2 presents preliminary SUR estimates of the transmission elasticities per wheat type.

Table 2: Cross-level yield elasticities (MS → E15, MS → NMS) for soft and durum wheat: SUR estimates

Equation	*$lnYLD_{ms}$*	*Member state*	*R^2 (ΔR^2)*
E15_WTS	0.388	France	0.95 (+86%)
	0.265	Germany	
	0.175	United Kingdom	
	0.059	Spain	
NMS_WTS	0.410	Poland	0.99 (+36%)
	0.193	Romania	
	0.245	Hungary	
E15_WTD	0.832	Italy	0.97 (+28%)
	0.229	Spain	
NMS_WTD	0.681	Hungary	0.77 (+32%)

Note: The dependent variable in every equation is the group-mean yield of wheat (t/ha, logarithmized). Intercepts, trend and price coefficients are omitted from the Table to keep the focus on the yield-transmission elasticities. ΔR^2 is the improvement in the explanatory power of the standard Aglink equations upon including the displayed MS-level yields as predictors. Time-series sample: n = 19 years (1995-2014). Estimates are significant at least at the 0.05 level (homoskedastic VCE).

Source: Own estimation based on JRC (2016), FAO (2016), and Zampieri et al. (2016).

The next step is to create 8 reduced-form[10] yield equations for the above MS using FAOSTAT yield data and our heat indices:

$$lnYLD_{wt,ms,t} = a_{wt,ms} + b_1*T + b_2*XW_{wt,ms,t} + lnR_{wt,ms,t} \quad (14)$$

[10] Price clearing still takes place at the EU level.

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where *ms* is the member-state identifier. Extreme weather, therefore, impacts MS-level yields through Eq. (14), which then transmits the effect on Eqs. (10) through (13) via the cross-level elasticities of Table 2. Preliminary estimates of the corresponding yield-to-heat partial effects are displayed in Table 3.

Table 3: Yield-to-heat partial effects: preliminary SUR estimates for key EU member states

Region	***HWMId***	***R^2 (ΔR^2)***	***HW timing***
FRA	*ns*	-	-
DEU	-0.007	0.80 (+5%)	5.0 – 8.0
GBR	*ns*	-	-
ESP	-0.058	0.50 (+18%)	3.9 – 6.9
ITA	-0.019	0.61 (+16%)	3.9 – 6.9
POL	-0.010	0.43 (+18%)	5.0 – 8.0
ROU	-0.033	0.45 (+44%)	4.9 – 7.9
HUN	-0.011	0.29 (+10%)	5.0 – 8.0

Note: The dependent variable is the mean national yield of wheat (t/ha, logarithmized). Intercepts and trend coefficients are omitted from the Table to keep the focus on the *HWMId* coefficients. ΔR^2 is the improvement in the explanatory power of the only-trend specifications upon including *HWMId* as an additional predictor. The column *'HW timing'* shows the three-month windows over which the heat index was computed (1 = January). Time-series samples: n = 30 years (1981-2010). Estimates are significant at least at the 0.05 level (homoskedastic VCE).

Source: Own estimation based on JRC (2016), FAO (2016), and Zampieri et al. (2016).

4. An empirical example: Australian heat wave in 2017

With the preliminarily calibrated model in hand, we now turn to an illustrative simulation of the market impacts of a counterfactual single-region (Australia) single-crop (wheat) single-year shock in Australia. In the 2017-2026 baseline, the heat index takes on the value of its historical mean (=4.9), which can be thought of as a representation of typical heat conditions in wheat-growing areas. In the scenario, the index takes on its historical maximum value (=8.7) in first simulation year (2017) and its historical mean value in the remaining years (2018-2026). The simulated impacts of such a counterfactual heat wave on the domestic and global wheat markets are shown in Figures 1 and 2. Unless mentioned otherwise, we focus on the short-term market impacts.

On the domestic market (Figure 1), a severe heat wave in 2017 would lead to significant yield reduction compared to the baseline (-34.4%). This figure implies a proportionate drop in total production (see identity Eq. 1). Lower production quantities would, in turn, lead to a 14.5% decline in per-hectare returns along with a 8.7% increase in producer (farm-gate) prices. By construction of the heat index, the heat wave is assumed to hit farmers after the execution of planting decisions. Therefore, no land re-allocation is observed in the first simulation year; Eqs. (8) and (5), however, prescribe a lagged land re-allocation –in this case, from wheat to barley, oats and other coarse grains– in the subsequent three years, which is driven by the 2017 drop in per-hectare wheat returns. Changes in total consumption of wheat are exclusively realized on feed use, which declines by 2.4%. This change in feed demand goes along with relatively weak cross-price effects regarding feed substitutes. Indicatively, the prices of DDGs, maize and other grains rise by up to 1.8% compared to the baseline.

Although Australia would remain a net exporter with unchanged near-zero imports, exports would roughly halve following the heat wave (Figure 2). This leads to a reduction of 2.4% in world trade, a reduction of 2% in world stocks, and to a subsequent increase of 5.4% in the world price. Australian wheat exports have historically been dependent on Indonesian, Vietnamese and Chinese import demand. Therefore, at a later stage, and in light of the growing Asian (import) demand, it would be interesting to further investigate the

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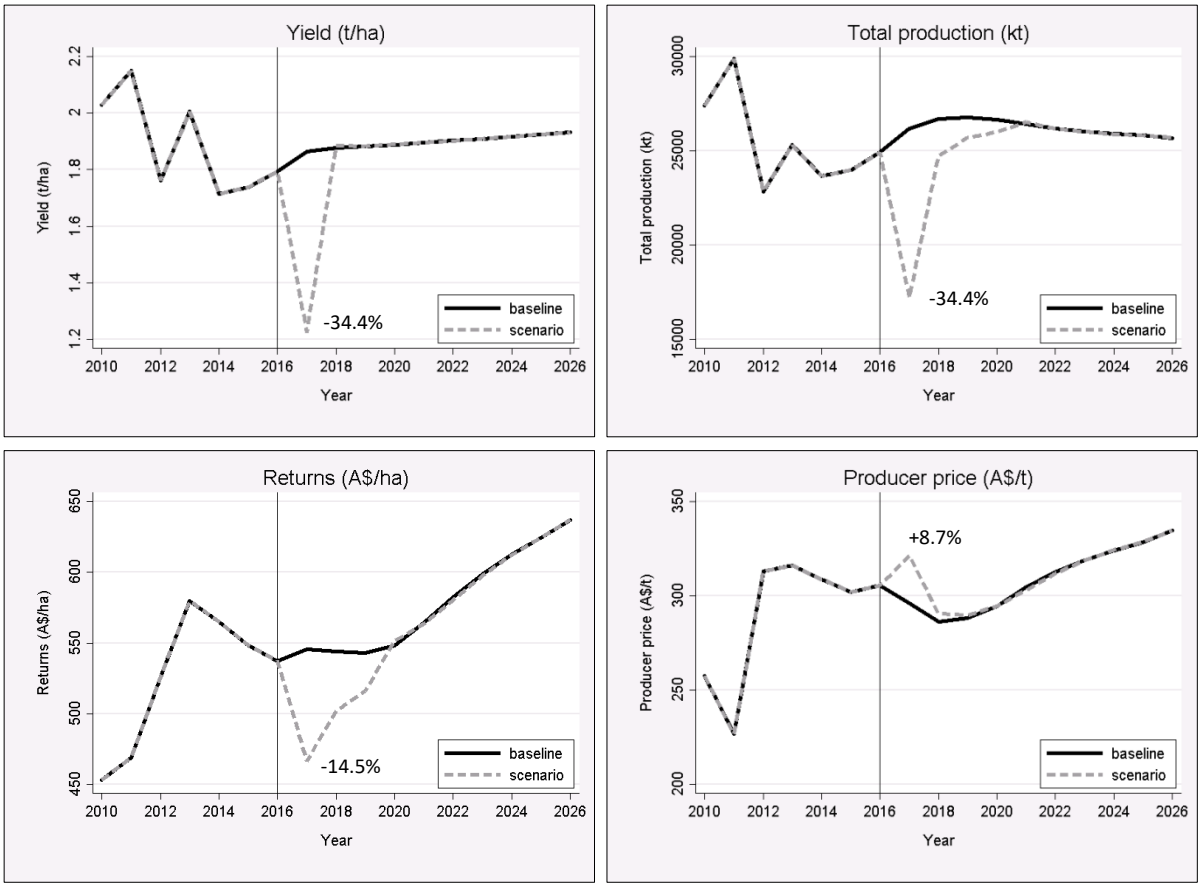
strong competition Australia would face from other key exporters such as the US, the EU, and the Black Sea region.

The two main shortcomings of this illustrative scenario are as follows. First, global market effects generally fall short of the corresponding effects on the domestic market. This was somewhat expected because although wheat exports typically account for 50-80% of the Australian wheat production, Australian exports constitute around 11% of global exports. Second, both the domestic and global market figures stabilize relatively smoothly after the heat wave. This can be attributed to the nature of the shock which is assumed to hit one (exporting) country and to affect the growing conditions of one crop. With the implementation of region- and crop-concurrent shocks (i.e., S3 in Table 4), we expect the market effects at the domestic and global levels to be more intricate.

Table 4: Scenario setting

	Multi-scenario	***The extreme-weather shock is performed for the first simulation year on…***
S1	Single-region single-crop	…one region and one crop at a time
S2	Single-region multi-crop	…one region and many crops at a time
S3	Multi-region multi-crop	…many regions and many crops simultaneously



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-7.8%

-46%

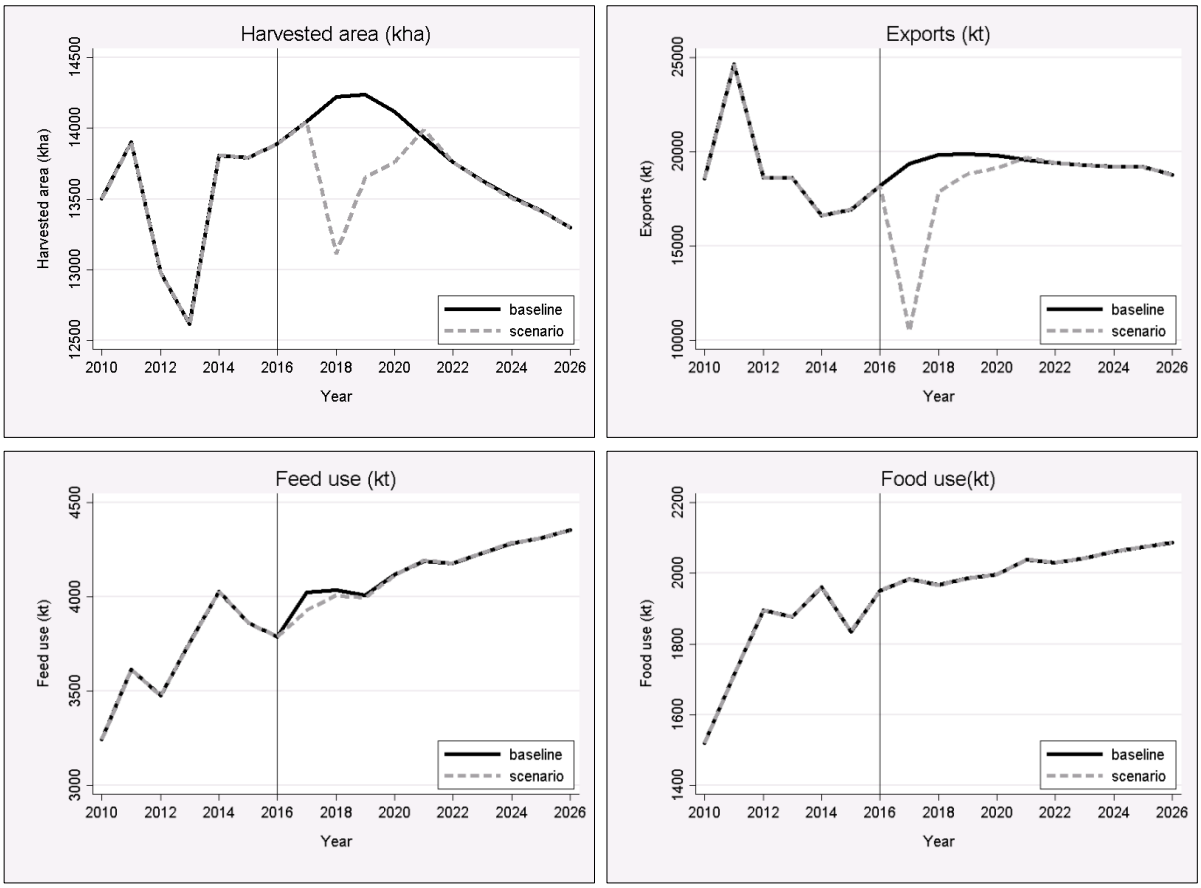

Figure 1: Australian heat wave in 2017 – potential impacts on the domestic wheat market

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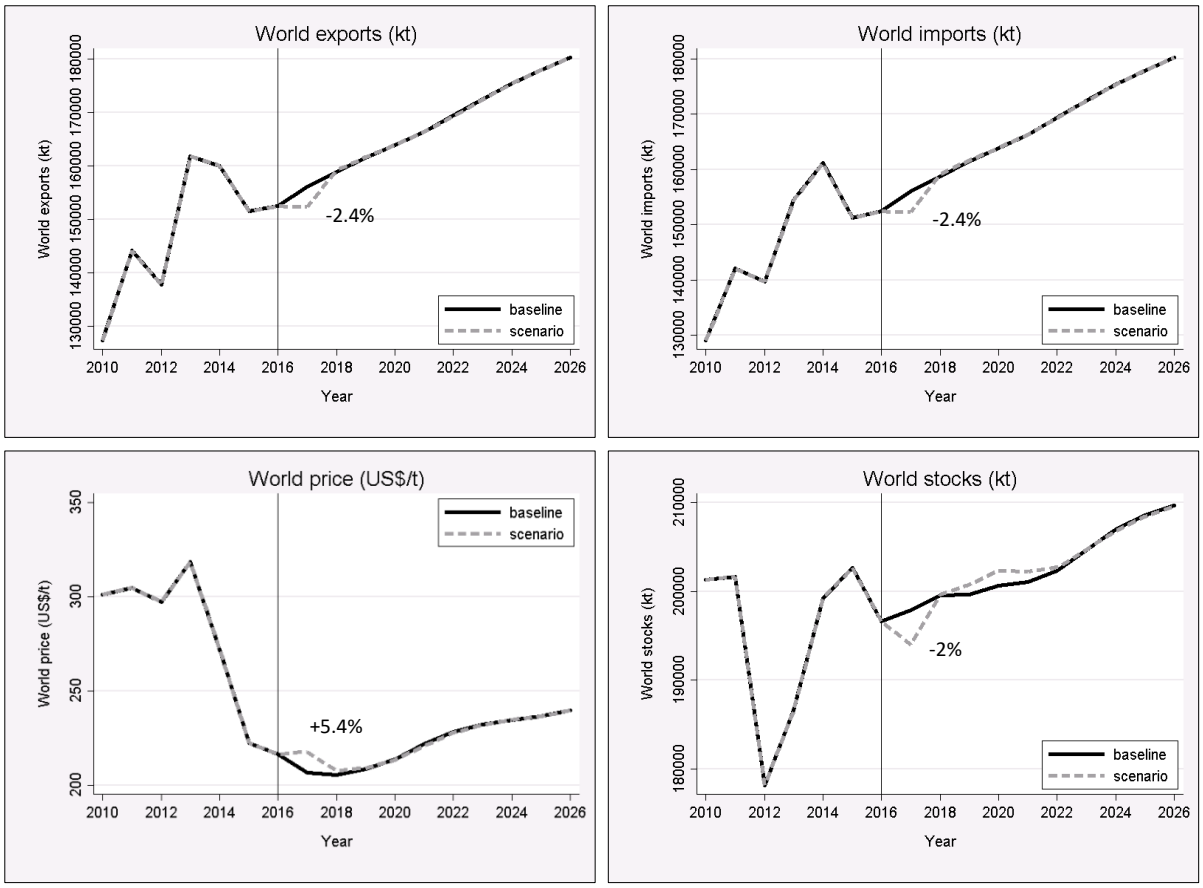

Figure 2: Australian heat wave in 2017 – potential impacts on the world wheat market

5. Challenges and upcoming work

- *Irrigation/water*: The Aglink-Cosimo modelling system does not differentiate between rainfed and irrigated crops, and the newly parameterized heat index is temperature-based. In conjunction with short yield series, these are the reasons why our estimates of yield-to-heat elasticities for some key producers may be deemed low or statistically not significant (e.g., Ukraine). On the one hand, wheat producers in some countries, mainly in the subtropics, rely heavily on irrigation and can generally adapt to heat stress by irrigating more. On the other hand, many regions face severe droughts (i.e., precipitation deficits) which are only partially correlated with heat waves. Alternative methods and indices will be used to estimate the sensitivity of key regions to both phenomena.
- *Damage-function approach*: Although it would be interesting to consider a global or regional damage-function approach, different extreme-weather indices explain yield variation in different regions (e.g., USA vs. Canada). This happens because there is no unique definition for extremeness, which is relative and depends heavily on the context. A damage-function approach is easier to implement with unidimensional weather variables (e.g., average temperature) than with extreme-weather indices.
- *Baseline*: It is difficult for climate science to predict with high confidence the extent of occurrence, frequency, and intensity of extreme weather events in individual regions over a decade ahead, which is the operational time horizon in Aglink. However, the values of the extreme-weather indices could be kept at their historical means or at zero for generating baseline projections. Zero values would explicitly reinforce the absence of heat waves.

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- *Partial stochastic analysis*: To take into account historical uncertainties that accompany agricultural commodity markets, Aglink-Cosimo is supplemented with a partial stochastic analysis module that runs independently. It will be challenging to adapt this module to the new heat-wave variables and new and updated yield equations. We hope to move in this direction in the future.
- We will test further extreme-weather indices (e.g., drought, excessive wetness) and additional key crops (maize, rice, soybeans) in the future.

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