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Analysis

Understanding agricultural market dynamics in times of crisis: The dynamic agent-based network model *Agrimate*

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ABSTRACT

The concentration of crop production in a few global breadbaskets and strong import dependencies of many developing countries render global grain markets susceptible to systemic shocks from weather- or conflict-induced supply failures. Often amplified by unilateral policy responses, such as export restrictions, the resulting short-term risks to global food security are substantial but insufficiently captured by established modeling approaches. Here, we present *Agrimate*, a dynamic agent-based agricultural market model. Explicitly accounting for commercial and strategic stockholding, and endogenously modeling supply- and demand-side responses, *Agrimate* describes the spreading of supply failures in international grain trade networks and associated price effects with high temporal resolution. For the major food grain wheat, we show that *Agrimate* can quantitatively reproduce monthly world market price hikes and annual changes in regional supply, consumption, and stocks during the 2007/08 and 2010/11 world food crises. Further, we study potential food security risks arising from multi-breadbasket failures. We find that in a +2 °Cworld, the risk of severe (90th percentile) price hikes more than doubles, while the risk of severe regional consumption losses increases by up to 130%, compared to 2006–2015 climate conditions. Our modeling shows that *Agrimate* can provide policy-relevant insights into the spreading of food security risks.

1. Introduction

World food markets are fragile to systemic shocks due to a concentration of production in a few main breadbasket regions and resulting import dependencies of many developing countries of the Global South (Puma et al., 2015). Supply failures and associated price spikes due to weather-induced crop failures in one or several breadbaskets and amplified by uncoordinated and unilateral policy responses such as export restrictions pose significant risks to food security globally (FAO et al., 2013), and especially in strongly import-dependent low-income countries in Asia and Africa (d'Amour and Anderson, 2020).

In the beginning of the twenty-first century, global food security was jeopardized by two major world food crises – in 2007/08 and in 2010/11 (FAO, 2012). Both crises were preceded by simultaneous harvest failures in several main producing regions (global breadbaskets). The resulting market uncertainties caused major net-exporters to issue export restrictions, seeking to protect domestic consumers against high world market food prices. This decreased the amount of food available at international markets and caused sharp increases in food prices (Tadesse et al., 2014). These resulted in food riots undermining social stability in multiple import-dependent low- and middle income countries, mainly in North- and Sub-Saharan Africa and South-East Asia (Paveliuc Olariu, 2013). The risk of such simultaneous harvest failures in major producing regions – in the following referred to as multi-breadbasket failures – has already increased (Gaupp et al., 2020) and is projected to further rise under global warming (Gaupp et al., 2019).

Due to the seasonality of crop production, models aiming to capture these short-term risks to food security have to explicitly account for storage, ideally differentiating between commercial and strategic (food security) stocks due to their different management rationales (Hayek et al., 2020; Hasegawa et al., 2020). Moreover, international trade plays an important role to mitigate the risk of global and local production failures and ensure food security in import dependent countries (Smith and Glauber, 2020; Baldos and Hertel, 2015; Sartori et al., 2024). At the same time, import dependencies expose countries to cross-border food security risks, especially if these have a non-diversified supplier base (Brown et al., 2017; Challinor et al., 2017). Thus, trade relations have to be highly resolved, spatially and temporally. Finally, food crises manifest themselves as reductions in physical food availability but also in the inaccessibility of food for poorer parts of the populations when food prices spike in times of tight markets (FAO et al., 2013). To this

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end, supply failures and associated price dynamics have to be modeled consistently to account for risks to both food availability and food access (Distefano et al., 2018).

Within the plethora of food security modeling approaches, models with the ability to comprehensively describe the short-term impacts of various climate- or socioeconomic-driven shocks are still missing at the global scale (Müller et al., 2020; Section 2). Designed to assess long-term challenges to food security arising from environmental factors such as climate change impacts or soil degradation but also socioeconomic pressures such as population growth and dietary change, general or partial-equilibrium agricultural integrated assessment models (e.g., Bond-Lamberty et al., 2022 or Dietrich et al., 2022) are not able to resolve short-term impacts of supply failures such as supply shortages and price spikes with sub-annual resolutions. Network-based approaches allowing to assess cascading supply failures (e.g., d'Amour et al., 2016) usually do only describe changes in supplied quantities and cannot account for price effects such as scarcity driven price inflation. Further, they often neglect the buffering effect of storage. The latter is well captured by competitive storage models (e.g., Wright and Williams, 1982). However, as equilibrium models, competitive storage models cannot account for out-of-equilibrium price dynamics such as scarcity driven price inflation. By contrast, describing the economy as a complex network of heterogeneous interacting agents with bounded-rational expectations, agent-based network models of the world economy (e.g., Hallegatte, 2014 or Otto et al., 2018) allow for demand-supply mismatches to occur leading to out-of-equilibrium trade and price dynamics. However, these models can currently not capture the peculiarities of agricultural markets, such as seasonality of production and trade, and the mixture of commercial and strategic stock-keeping.

Here, we aim to narrow this research gap by introducing *Agrimate*, a novel agent-based network model describing the short-term non-equilibrium dynamics of trade, consumption, and prices at agricultural markets for individual grains in the aftermath of systemic shocks (Tadesse et al., 2014; Headey, 2011; Lagi et al., 2015; Nayak and Waterson, 2019; Nolan et al., 2009; Pichler et al., 2022). We first introduce the main decision rationales of the economic agents and describe their interactions before calibrating the model to wheat, which is one of the most important food staples and the most traded grain at international markets (USDA, 2023). We then employ the model to hindcast the 2007/08 and 2010/11 world food price crises and show that the model can quantitatively reproduce short-term price volatility at the world market as well as changes in supply, consumption, and associated storage movements at global and regional levels. At the example of the exporter–importer relationship between Russia and Egypt, we explore how these dynamics emerges from the interaction of the market participants. Further, we show that export restricting nations may reduce their domestic food security risks, leading to higher losses in wheat consumption and storage for import-depending countries. We quantify the extent to which production anomalies and export restrictions contributed to the world market price hikes in each year of the crises. Finally, we assess changes in food security risks in terms of price spikes and consumption declines due to the increased likelihood of multi-breadbasket failures in a +2 °C world compared to historical climate conditions of the period 2006–2015. Our results suggest that *Agrimate* can be used for the rapid evaluation of food security risks during the initial stages of crises (e.g., food price crisis at the beginning of the Russian invasion of Ukraine in early 2022) or for analyzing short-term risk factors (e.g., aggravated climate-induced crop failures) along food system transformation pathways.

The remainder of the paper is structured as follows: We first discuss in the relevant literature on the modeling of agricultural markets, with a special focus on international agricultural trade in Section 2. Then, we describe the details of the *Agrimate* model in Section 3 as well as the initialization and input data it needs in Section 4. In Section 5, we present the results of the hindcasting exercise as well as the results of our analysis of the food security risks induced by the increased likelihood of multi-breadbasket failures under global warming. Finally, we discuss the results and our modeling approach in Section 6 before concluding in Section 7.

2. Related literature

2.1. General or partial-equilibrium agricultural integrated assessment models

General-equilibrium models like the model of the *Global Trade Analysis Project* (*GTAP*) (Corong et al., 2017) or the *Global Change Analysis Model* (*GCAM*) (Calvin et al., 2019; Bond-Lamberty et al., 2022), or partial-equilibrium agro-economic models such as the *Agricultural Linkage - Commodity Simulation Model* (*Aglink-Cosimo*) (OECD and FAO, 2022), the *Common Agricultural Policy Regionalised Impact Model* (*CAPRI*) (Barreiro-Hurle et al., 2021), the *Global Biosphere Management Model* (*GLOBIOM*) (Havlík et al., 2018; IIASA, 2018), or the *Model of Agricultural Production and its Impact on the Environment* (*MAgPIE*) (Dietrich et al., 2019, 2022) address the questions of long-term trends of the world food system. For instance, with those models it can be shown that reducing consumption of livestock products can lead to a halving of deforestation caused by agricultural land-use (Weindl et al., 2017), that biofuels may increase food prices modestly (Wise et al., 2014), or that weak governance may cause rising food prices in Sub-Saharan Africa and Southeast Asia (Wang et al., 2016). From the agricultural trade perspective, studies based on the *MAgPIE* model suggest that international trade of food crops saves blue water worth 2.4 billion US$ (Biewald et al., 2014) and that food import dependencies in countries of the Global South will likely increase under climate change (Pradhan et al., 2014). Because of their broad scope, those models are characterized by a high complexity representing all the relevant interconnections between the economy, land use, and agricultural activities. Moreover, most of them operate on very coarse time scales. For instance, *GLOBIOM* and *MAgPIE* are usually run with decadal resolution. However, some agricultural integrated assessment models can also be run with annual resolution, such as the stochastic *Aglink-Cosimo* (Araujo-Enciso and Fellmann, 2020) and *GLOBIOM-X* (Boere, 2021) to assess the impacts of weather-induced production shocks. However, these models still do not allow resolving weather-, conflict-, and policy-induced supply failures and associated scarcities and price effects at sub-annual resolution.

2.2. Competitive storage models and other dynamical agricultural market models with storage

There is a large body of literature employing variants of the competitive storage model (Wright and Williams, 1982) – as one of the standard models in agricultural economics – to assess year-to-year price volatility at agricultural markets of individual food staples. The model allows reproducing the characteristic skewed and fat-tailed distributions of annual world market prices of food staples well (Cafiero et al., 2011) but has difficulties to reproduce historical price time series quantitatively. Extended versions of the model were successfully used to assess the mitigating potential of regional stocks in times of crises (Gouel, 2016; Gouel and Jean, 2012; Larson et al., 2013; Porteous, 2019; Wright and Cafiero, 2011; Wright, 2012). A simplified implementation of a competitive storage model has been applied by Porteous (2019) to agricultural markets in Sub-Saharan Africa with a monthly resolution; it identified trade costs as a key factor responsible for high prices of agricultural goods in that region of the world. Similarly, the multi-sectoral *Food Distributed Extendable Complementarity* (*Food-DECO*) model has been introduced as a tool to assess supply shock impacts on food security in Ethiopia on monthly timescales (Bakker et al., 2018). Both of those models are state-of-the-art tools to uncover the sub-annual dynamics of food systems in Sub-Saharan Africa and Ethiopia, respectively. However, as by design, they do not allow accounting for non-rational decisions and non-equilibrium price dynamics and scarcity situations. Further, the computational expense of the inter-regional and inter-temporal (and multi-sectoral in the case of *Food-DECO*) optimization inherent to this type of models makes it challenging to increase their regional and temporal coverage or to run large ensembles of simulations as needed for risk assessments. The *Trade With Storage* (*TWIST*) model of trade and storage based on a stylized price-supply curve can explain the evolution of the world market wheat prices at the annual time resolution, but cannot describe regional price, supply and consumption changes and storage movements (Schewe et al., 2017; Falkendal et al., 2021; Kuhla et al., 2024).

2.3. Network and agent-based models

Agent-based models (ABMs) are computational models used to simulate interactions among heterogeneous agents, which can represent a group of people, institutions, or other entities with decision-making capabilities (Bonabeau, 2002; Railsback and Grimm, 2019). Each agent follows a set of rules, and the overall dynamics of the studied system emerges from the agents' interactions. This approach is particularly useful for capturing complex behaviors, heterogeneity among agents, and the decentralized interactions typical for socio-economic systems. In the context of food systems, the model *agriculture and organization in an evolutionary economy* (*AgriLOVE*) describes a lock-in mechanism, where farmers adopt practices that exacerbate soil degradation, resulting in an increase of food scarcity and prices (Coronese et al., 2023). Further, the agent-based model *Acclimate* (Otto et al., 2018) is, in principle, suited to assess the cascading impacts of production shocks in the trade network, including price effects and endogenous demand responses; however, it cannot represent the peculiarities of agricultural markets where the concentration of production in the harvest season and storage jointly determine seasonal price and trade patterns (Piot-Lepetit and M'Barek, 2011).

There are a few models that address food system shocks beyond the equilibrium paradigm. Such models like the *Food Stock Cascades* (*FSC*) model (Puma et al., 2015; Heslin et al., 2020), the relation-driven trade model by Ge et al. (2021), and the network model by d'Amour et al. (2016) simulate a redistribution of demand in the trade network in the aftermath of changing export patterns. Their results provide insights into the risks of import dependencies and help to identify particularly vulnerable "hot spot" countries. However, they do not describe the price dynamics and resulting demand responses and cannot describe sub-annual market dynamics.

The agent-based agricultural trade model *Agrimate* introduced here aims to address many of the shortcomings of existing modeling approaches. Unlike general- or partial-equilibrium agricultural models or static network models, *Agrimate* provides the ability to assess short-term (e.g., weekly to monthly) risks to food security arising from weather-, conflict- or, trade-induced supply failures. Further, contrary to integrated assessment and competitive storage models, *Agrimate* allows simulating out-of-equilibrium dynamics resulting for instance from supply–demand mismatches. By explicitly modeling heterogeneous regional competitive and strategic storage holders and consumers and their interactions within complex trade networks, *Agrimate* allows assessing not only global but also regional food security risks. Compared to other existing agent-based trade models, *Agrimate* is able to reproduce stylized facts of agricultural markets, like the seasonality of crop trade or the heterogeneity of national storage policies. In this regard, *Agrimate* significantly expands the current modeling landscape.

3. Model description

Here we provide a summarizing narrative of the *Agrimate* model. A complete in-detail model description, following the ODD (Overview, Design concepts, Details) protocol (Grimm et al., 2006, 2020), can be found in Suppl. Sec. D.

3.1. Model objectives and key modeling decisions

We take an agent-based modeling approach because it allows accounting (i) for regional heterogeneity with regard to stockholding policies and market power, and (ii) to capture short-term non-equilibrium dynamics in the aftermath of weather- and policy-induced supply failures. To limit the complexity of the *Agrimate* model and facilitate its calibration, we describe the dynamics of domestic and international markets for individual staple crops. In the main text, we present the results for wheat as the internationally most traded food grain (USDA, 2023), while the results for rice, maize, and soybean are presented in Suppl. Sec. G. The model is an anomaly model in the sense that it describes deviations from a periodic baseline state driven by the annual production cycle and does not account for changes in the network topography over time. The model is forced by production anomalies and temporal changes in trade policies, such as export restrictions. Market seasonality can only be grasped if agents form expectations on future market developments for at least one agricultural year. This expectation formation is modeled as an adaptive process, where agents adapt their market decisions in each time step based on their gain in information. The modeling period is application-dependent, but for historical analysis it should be taken into consideration that the model assumes a static baseline network and currently does not account for longer-term topographical changes of the underlying trade network.

3.2. Agents' rationales

Agrimate is global and spatially resolves individual countries or country groups. In the following, we refer to the basic spatial unit of the model as *region*. Each region has a producer-site commercial storage holder (*supplier*), a consumer-site strategic storage holder (*purchaser*), and a domestic *consumer*. We assume a demand-driven economy where non-equilibrium dynamics such as supply–demand mismatches can occur in crises situations. The key endogenous producer-site variables are, sales, expected sales, offer price, and commercial storage, and the key consumer-site variables are demand, purchase, strategic storage, consumer price and consumption.

The trade and associated price dynamics emerges from the interaction of the three types of heterogeneous agents. At the beginning of each time step, the suppliers receive (i) the regions' harvests in the current time step, and (ii) the demand requests which their trade partners – i.e., the purchasers they are connected to – have sent at the end of the previous time step. They fulfill these demand requests up to their capacity. If they cannot meet the incoming demand, they first fulfill the demand of their domestic purchaser and then ration their remaining supplies proportionally to the quantities demanded by their international purchasers. Next, they inter-temporally maximize their expected profit to determine their optimal sales over their foresight period (Section 3.2.1). To keep the optimization problem tractable, they assume that there is a single world market, and that all other suppliers have access to their domestic market. In their expectation formation, they account for the expected supplies to these markets which their competitors – i.e., all other suppliers in the model – have communicated for their foresight period. If agents expect their future total supplies to international markets to be restricted by export restrictions, they adjust them accordingly before communicating them to the other market participants. Next, each supplier uses the information on the expected supplies of its competitors to formulate its offer price for the next time step and communicate it to its purchasers. Through the exchange of information on offer prices and expected supplies, the agents also transfer information on (i) local scarcities and abundances resulting from weather-induced regional production failures or better-than-usual productions, respectively, and (ii) export restrictions among the market participation. Thus, this exchange mimics the spreading of information through future markets (Ahlers et al., 2013).

In parallel, the regional consumers determine their consumption level based on a nested constant elasticity of substitution (CES) utility function under a budget constraint, accounting for their local consumer prices. They thereby have only access to the region's consumer-site storage and cannot send own demand requests to suppliers. Thus, their consumption is capped by the storage content (Section 3.2.2).

Finally, the regional purchasers determine their demand for the next time step, accounting for the supplies that are shipped to them and deviation of the storage content from its baseline value (storage anomaly). They then decide upon the distribution of their demand among their suppliers by maximizing a CES utility function under a budget constraint (Section 3.2.3). In their decision formation, they account for their suppliers' (i) demand shares in the baseline network, (ii) offer prices, and (iii) anomalies of planned next time step's total supplies from their respective baseline values. Accounting for the baseline demand shares allows including purchasers' preferences for suppliers – for instance due to long-standing trade relationships – which are not endogenously resolved in the model, and accounting for expected supply anomalies allows purchasers to shift their demand to unaffected supplier, e.g., when a supplier is affected by a production failure or export restriction.

In the following, we provide a motivational overview of the agents' decision rationales, which are formulated as three local optimization problems. A detailed model description can be found in Suppl. Sec. D.

3.2.1. Supplier's problem

Region r's supplier is modeled as a risk-neutral, bounded rational, profit-maximizer with adaptive expectations. In each time step t, it maximizes its expected profit $\hat{\Pi}^{(t)}$ over the N_{hor} time steps of its foresight period to obtain its optimal expected domestic supplies $\left\{\hat{X}^{(t+n)}_{\text{opt,D},r}\right\}_{n=1}^{N_{\text{hor}}}$ and its expected total international supplies, $\left\{\hat{X}^{(t+n)}_{\text{opt,I},r}\right\}_{n=1}^{N_{\text{hor}}}$ under the constraint that its expected storage content has to remain non-negative. The corresponding constrained maximization problem reads,

$$\left\{\hat{X}^{(t+n)}_{\text{opt,D},r}, \hat{X}^{(t+n)}_{\text{opt,I},r}\right\}_{n=1}^{N_{\text{hor}}} = \underset{\hat{X}'^{(t+n)}_{\text{D},r}, \hat{X}'^{(t+n)}_{\text{I},r}}{\operatorname{argmax}} \left[\hat{\Pi}^{(t)}_r\left(\left\{\hat{X}'^{(t+n)}_{\text{D},r}, \hat{X}'^{(t+n)}_{\text{I},r}\right\}_n\right)\right] \tag{1a}$$

$$\text{s.t.} \quad 0 \le \hat{X}'^{(t+n)}_{\text{D},r} + \hat{X}'^{(t+n)}_{\text{I},r} \le \hat{H}^{(t+n)}_r + \sum_{m=1}^{n-1}(1-\delta)^{n-m}\left(\hat{H}^{(t+m)}_r - \hat{X}'^{(t+m)}_{\text{D},r} - \hat{X}'^{(t+m)}_{\text{I},r}\right) + (1-\delta)^{n+1} S^{(t)}_{\text{p},r}, \tag{1b}$$

where δ denotes the spoilage rate of the stored commodity, $\hat{H}^{(t+n)}_r$ and $S^{(t)}_{\text{p},r}$ denote its expected domestic harvest in time step $(t+n)$ and ending stock in the current time step, respectively. Further, the supplier's expected profit is the sum of expected revenues net of storage costs over the N_{hor} time steps of the foresight period,

$$\begin{aligned}\hat{\Pi}^{(t)}_r\left(\left\{\hat{X}'^{(t+n)}_{\text{D},r}, \hat{X}'^{(t+n)}_{\text{I},r}\right\}_n\right) = \\ \sum_{n=1}^{N_{\text{hor}}}(1+\rho)^{-n}\cdot\left[\hat{P}_{\text{D},r}\left(\hat{X}'^{(t+n)}_{\text{D},r}\right)\cdot\hat{X}'^{(t+n)}_{\text{D},r} + \hat{P}_{\text{I},r}\left(\hat{X}'^{(t+n)}_{\text{I},r}\right)\cdot\hat{X}'^{(t+n)}_{\text{I},r}\right] \\ + p_{\text{sto}}\cdot\sum_{n=1}^{N_{\text{hor}}}(1+\rho)^{-n}\cdot\frac{1-\gamma^{N_{\text{hor}}+1-n}}{1-\gamma}\cdot\left(\hat{X}'^{(t+n)}_{\text{D},r} + \hat{X}'^{(t+n)}_{\text{I},r}\right) \\ - \zeta\left(\hat{X}'^{(t+n)}_{\text{D},r}, \hat{X}'^{(t+n)}_{\text{I},r}\right),\end{aligned} \tag{2}$$

where p_{sto} and ρ are the price to store a unit of the commodity and the interest rate per time step, respectively, and $\gamma = (1-\delta)/(1+\rho)$. The penalty function $\zeta\left(\hat{X}'^{(t+n)}_{\text{D},r}, \hat{X}'^{(t+n)}_{\text{I},r}\right)$ reduces the profit if expected sales at any time step fall below a certain threshold, in order to suppress extreme decision such as selling all the available grain within one time step, which stabilizes the behavior especially of small storage holders with little impact on the world market price. Further, in its expectation formation, the supplier makes the simplifying assumption of a common world market by neglecting the network structure of the trade connections. Noteworthy, this assumption affects only the expectation formation, and the actual international market of each supplier still depends upon its trade network. This is why we denote this expected price as supplier r's expected international market price. The prices supplier r expects at its domestic (D) and international (I) markets,

$$\hat{P}_{\text{D/I},r}\left(\hat{X}'^{(t+n)}_{\text{D/I},r}\right) = \left(\frac{\hat{X}'^{(t+n)}_{\text{D/I},r} + \hat{X}^{(t+n)}_{\text{D/I,oth},r}}{\overline{X^*_{\text{D},r/\text{I}}}}\right)^{-\alpha_{\text{D},r/\text{I}}}, \tag{3}$$

are described by isoelastic inverse demand functions with the inverse of price elasticities of demand $\alpha_{\text{D},r/\text{I}}$. (Note that all prices in the model are unitless indices with a magnitude of order one.) The price functions incorporate the total supplies $\hat{X}^{(t+n)}_{\text{D/I,oth},r}$ which supplier r's competitors are expecting to supply to r's domestic market and international market, respectively. The normalization constants $\overline{X^*_{\text{D},r/\text{I}}}$ for region r's domestic and international markets are its baseline domestic consumption and the total baseline sales to international markets, i.e., the sum of all supplies to international markets averaged over the agricultural year, respectively.

Export restrictions are modeled as quantity restrictions (cf. Suppl. Sec. D.6 for details). If the supplier expects that restrictions will be issued by its regional government in the following time steps, it adapts the expected domestic and total international supplies by transferring the expected restricted amount of its total optimal international supplies $\hat{X}^{(t+n)}_{\text{opt,I},r}$ to its domestic market,

$$\hat{X}^{(t+n)}_{\text{I},r} = \left(1-\hat{\Delta}^{(t+n)}_r\right)\cdot\hat{X}^{(t+n)}_{\text{opt,I},r} \quad \& \tag{4a}$$

$$\hat{X}^{(t+n)}_{\text{D},r} = \hat{X}^{(t+n)}_{\text{opt,D},r} + \hat{\Delta}^{(t+n)}_r\cdot\hat{X}^{(t+n)}_{\text{opt,I},r} \quad \text{for } n \in \left[1,\ldots,N_{\text{hor}}\right], \tag{4b}$$

where $0 \le \hat{\Delta}^{(t+n)}_r \le 1$ denotes the share of restricted total international supplies in time step $(t+n)$ ($\hat{\Delta}^{(t+n)}_r = 0$ if no export restriction is expected in the region). Thereby, we assume that suppliers cannot foresee export restrictions. Once these are implemented, the supplier of the issuing region knows how long these restrictions will remain in place, but it cannot foresee any change in restrictions. Thus, it has to adapt its expectations on future export restrictions each time the restrictions are tightened or relaxed. This behavioral assumption is motivated by the observation that export restrictions are often used as short-term response measures in times of crises and are usually announced with an expiration date (e.g., end of local agricultural year for the considered commodity). However, once in place, their duration and severity is frequently adapted to changes in the market situation (AMIS, 2021).

Next, the supplier communicates its expected total international sales $\left\{\hat{X}^{(t+n)}_{\text{I},r}\right\}_n$ to the other market participants and is in turn informed on the expected total international supplies from all other suppliers.

This allows the supplier of region r to determine its next offer prices at the domestic and the international market by inserting its own expected domestic and international supplies for the next time step (Eq. (2)) together with the expected total supplies from other suppliers to its domestic and international markets into the corresponding price functions (Eq. (3)),

$$p^{(t+1)}_{\text{off,D/I},r} = \hat{P}_{\text{D/I}}\left(\hat{X}^{(t+1)}_{\text{D/I},r}\right). \tag{5}$$

Finally, it communicates the respective offer prices $p^{(t+1)}_{\text{off,D/I},r}$ to its purchasers.

The formulation of the suppliers' problem in *Agrimate* is similar to the well-established competitive storage model (Williams and Wright, 1991), with three major differences. First, in *Agrimate* the suppliers consider in their profit optimization their domestic market in addition to the world market, which allows accounting for regional export restrictions. Second, in *Agrimate*, the suppliers have a finite foresight horizon and adapt their expectations in each time step according to their gain in information. Third, in *Agrimate* , the markets are oligopolistic and not perfectly competitive: big suppliers influence prices more than small suppliers.

3.2.2. Consumer's problem

The consumer of the region s decides upon its consumption $C_s^{(t)}$ by maximizing a CES utility function under a budget constraint and a quantity constraint, reading

$$C_s^{(t)}, C_{\perp,s}^{(t)} = \underset{\tilde{C}_s^{(t)}, \tilde{C}_{\perp,s}^{(t)}}{\operatorname{argmax}} \left[U_{c,s}\left(\tilde{C}_s^{(t)}, \tilde{C}_{\perp,s}^{(t)}\right)\right] \tag{6a}$$

$$\text{s.t.} \quad p_{c,s}^{(t)} \cdot \tilde{C}_s^{(t)} + p_{\perp,c,s}^{(t)} \cdot \tilde{C}_{\perp,s}^{(t)} \leq B_{c,s}^* \quad \& \quad 0 \leq \tilde{C}_s^{(t)} \leq I_s^{(t)} + S_{c,s}^{(t-1)} \tag{6b}$$

$$\Rightarrow \quad C_s^{(t)} = \min\left[\frac{A_{c,s}^* \cdot \left(p_{c,s}^{(t)}\right)^{-\varepsilon_c}}{1 + A_{c,s}^* \cdot \left(\left(p_{c,s}^{(t)}\right)^{1-\varepsilon_c} - 1\right)} \cdot B_{c,s}^*, I_s^{(t)} + S_{c,s}^{(t-1)}\right]. \tag{6c}$$

Here, $C_s^{(t)}$ and $C_{\perp,s}^{(t)}$ denote the optimal consumption of the modeled agricultural commodity and a complementary compound good representing all other goods in the consumption basket, respectively, as obtained from maximizing the CES utility function

$$U_{c,s}\left(\tilde{C}_s^{(t)}, \tilde{C}_{\perp,s}^{(t)}\right) = \left(A_{c,s}^{*\,\frac{1}{\varepsilon_c}} \left(\tilde{C}_s^{(t)}\right)^{\frac{\varepsilon_c - 1}{\varepsilon_c}} + (1 - A_{c,s}^*)^{\frac{1}{\varepsilon_c}} \cdot \left(\tilde{C}_{\perp,s}^{(t)}\right)^{\frac{\varepsilon_c - 1}{ec}}\right)^{\frac{\varepsilon_c}{\varepsilon_c - 1}}, \tag{7}$$

where $A_{c,s}^*$ is the share of the consumer's budget $B_{c,s}^*$ spent on the commodity in the baseline state. The consumer's budget $B_{c,s}^* = \overline{p_{c,s}^{*,(t)} C_s^{*,(t)}} / A_{c,s}^*$ is fixed and equals the baseline consumption costs averaged over the year $\overline{p_{c,s}^{*,(t)} C_s^{*(t)}}$ divided by $A_{c,s}^*$. The amount of grain that s can consume is limited by the content of its strategic storage, i.e., the storage carryover from the previous time step $S_{c,s}^{(t-1)}$ plus supplies arriving at this storage in the current time step $I_s^{(t)}$. Further, ε_c denotes the elasticity of substitution between the considered commodity and the rest of the products in the consumer basket and may thus be interpreted as the price elasticity of consumption. Further, $p_{c,s}^{(t)}$ and $p_{\perp,c,s}^{(t)}$ are the consumer prices for the considered commodity and the compound good, respectively. As the consumer sources the considered commodity from the region's strategic storage $S_{c,s}^{(t)}$, the consumer price $p_{c,s}^{(t)}$ is the average price of the commodity in region s's strategic storage. Thus, the storage (i) reduces the spill-over of price volatility at international markets to the domestic consumer price and (ii) introduces a lag time. In line with empirical findings (Kalkuhl, 2016), both volatility reduction and lag time increase with stock-to-consumption ratio measuring the size of the storage relative to the region's consumption.

By inserting the above expression for the consumer's budget in Eq. (6c) and taking into account that $|\varepsilon_c| \ll 1$, we see that the consumption becomes more inelastic with increasing $A_{c,s}^*$, i.e., in the limit $A_{c,s}^* \ll 1$, consumption is elastic $C_s^{(t)} \sim \left(p_{c,s}^{(t)}\right)^{-\varepsilon_c}$, whereas, in the limit $A_{c,s}^* = 1$, it is basically inelastic $C_s^{(t)} \sim \left(p_{c,s}^{(t)}\right)^{-1}$. Thus, well in line with the empirical literature, it is more difficult for consumers in low-income countries to keep up their consumption in times of high international market prices than for consumers in high-income countries. First, because low-income countries have less financial means to protect their domestic consumers (e.g., by building-up strategic food security stocks) (Valdés and Foster, 2012). Second, because consumers in low-income countries have to spend (on average) a larger share of their income on food commodities (Ivanic and Martin, 2008).

3.2.3. Purchaser's problem

In each time step, the purchaser of each region s is charged with buying enough of the agricultural commodity to fulfill the region's domestic consumption in the next time step and to refill its storage. To this end, it has to decide upon the optimal distribution of its demand among its suppliers. Similar to the consumers' problem, the purchaser decides upon its optimal distribution of demands by maximizing a CES utility function under a budget constraint

$$\left\{D_{r\leftarrow s}^{(t+1)}\right\}_r, D_{\perp,s}^{(t+1)} = \underset{\left\{\tilde{D}_{r\leftarrow s}^{(t+1)}\right\}_r, \tilde{D}_{\perp,s}^{(t+1)}}{\operatorname{argmax}} \left[U_s\left(\{\tilde{D}_{r\leftarrow s}^{(t+1)}\}_r, \tilde{D}_{\perp,s}^{(t+1)}\right)\right] \tag{8a}$$

$$\text{s.t.} \quad \sum_{r\neq s} p_{\text{off},\text{I},r}^{(t+1)} \cdot \tilde{D}_{r\leftarrow s}^{(t+1)} + p_{\text{off},\text{D},s}^{(t+1)} \cdot \tilde{D}_{s\leftarrow s}^{(t+1)} + p_{\text{off},\perp,s}^{(t+1)} \tilde{D}_{\perp,s}^{(t+1)} \leq B_{d,s}^*. \tag{8b}$$

$$\Rightarrow \quad D_{r\leftarrow s}^{(t+1)} = a_{r,s}^{(t)} \cdot \left(\frac{p_{\text{off},r}^{(t+1)}}{p_{\to s}^{(t)}}\right)^{-\sigma} \cdot \frac{A_{d,s}^{(t)} \cdot \left(p_{\to s}^{(t)}\right)^{-\varepsilon_d}}{1 + A_{d,s}^{(t)} \cdot \left(\left(p_{\to s}^{(t)}\right)^{1-\varepsilon_d} - 1\right)} \cdot B_{d,s}^*, \tag{8c}$$

with price index

$$p_{\to s}^{(t+1)} = \left(\sum_{r\neq s} a_{r,s}^{(t)} \cdot \left(p_{\text{off},\text{I},r}^{(t+1)}\right)^{1-\sigma} + a_{s,s}^{(t)} \cdot \left(p_{\text{off},\text{D},s}^{(t+1)}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \tag{8d}$$

Here, $\left\{D_{r\leftarrow s}^{(t+1)}\right\}_r$ denote the demands for the considered agricultural commodity, which the purchaser will send out to its suppliers in the next time step, and $D_{\perp,s}^{(t+1)}$ denotes the total demand for a complementary compound good describing all other goods in the consumer's consumption bundle. Both are obtained by maximizing a CES utility function,

$$U_s\left(\{\tilde{D}_{r\leftarrow s}^{(t+1)}\}_r, \tilde{D}_{\perp,s}^{(t+1)}\right) = \left[\left(A_{d,s}^{(t)}\right)^{\frac{1}{\varepsilon_d}} \cdot \left(\sum_r \left(a_{r,s}^{(t)}\right)^{\frac{1}{\sigma}} \cdot \left(\tilde{D}_{r\leftarrow s}^{(t+1)}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}\cdot\frac{\varepsilon_d-1}{\varepsilon_d}} + \left(1 - A_{d,s}^{(t)}\right)^{\frac{1}{\varepsilon_d}} \cdot \left(\tilde{D}_{\perp,s}^{(t+1)}\right)^{\frac{\varepsilon_d-1}{\varepsilon_d}}\right]^{\frac{\varepsilon_d}{\varepsilon_d-1}}, \tag{9}$$

where $A_{d,s}^{(t)}$ is the share of the purchaser's total budget $B_{d,s}^*$ spent on the considered agricultural commodity in time step t. In the baseline state, the budget share $A_{d,s}^*$ is the ratio of the import value of the commodity to the value of the country's total exports. When in a crisis situation, the purchaser's storage level falls below its (time of the year dependent) baseline level, the purchaser temporally increases $A_{d,s}^{(t)}$ above its baseline level $A_{d,s}^*$ to refill the storage (cf. Suppl. Par. D.7.2.3). Further, σ and ε_d denote the price elasticity of substitution between supplies and the price elasticity of demand, respectively; the CES price index $p_{\to s}^{(t)}$ for purchaser s is determined by the offer prices $p_{\text{off},\text{D},s}^{(t)}$ and $\left\{p_{\text{off},\text{I},r}^{(t)}\right\}_{r\neq s}$ that were communicated by its domestic and its international suppliers, respectively, and $p_{\text{off},\perp,s}^{(t)}$ denotes the offer price of the complementary good. The share of demand $a_{r,s}^{(t)}$ directed towards supplier r under offer price parity depends upon (i) r's annually averaged supply share in the baseline state $a_{r,s}^*$ and (ii) the ratios of r's (total) expected sales to the domestic market $\hat{X}_{\text{D},r}^{(t)}$ and international markets $\hat{X}_{\text{I},r}^{(t)}$ (relative to the corresponding annually averaged supplies per time step in the baseline state $\overline{X_{\text{D},r}^*}$ and $\overline{X_{\text{I},r}^*}$), reading

$$a_{r,s}^{(t)} = \frac{a_{\text{nn},rs}^{(t)}}{\sum_{r'} a_{\text{nn},r's}^{(t)}} \quad \text{with} \quad a_{\text{nn},rs}^{(t)} = \begin{cases} \frac{\hat{X}_{\text{D},r}^{(t)}}{\overline{X_{\text{D},r}^*}} a_{r,s}^* & \text{for } r = s, \\ \frac{\hat{X}_{\text{I},r}^{(t)}}{\overline{X_{\text{I},r}^*}} a_{r,s}^* & \text{else.} \end{cases} \tag{10}$$

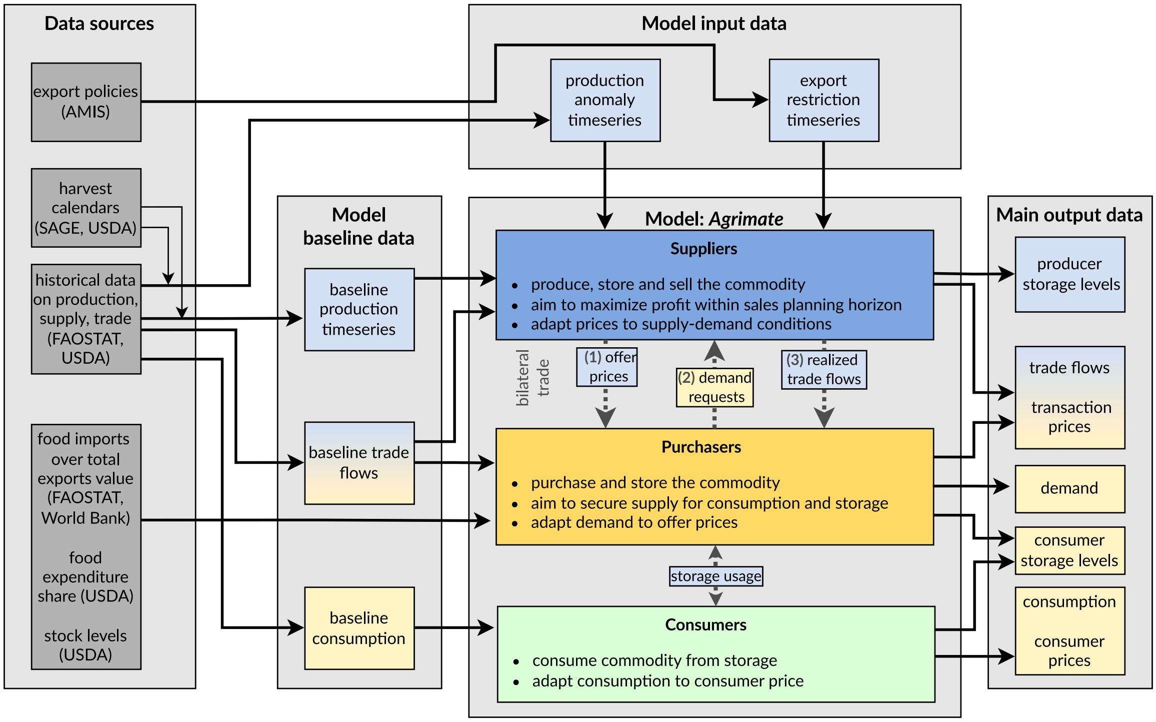

Fig. 1. Flow diagram describing inputs and outputs of the *Agrimate* model. Gray shaded boxes depict input data from various sources, whereas light blue (light yellow) boxes represent producer-site (consumer-site) in- and output data. The blue, yellow, and green boxes indicate the main decision points of the commercial storage holders (suppliers), strategic food security stockholders (purchasers), and the regional consumers (consumers), respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Grounded on well-established CES utility functions, the formulation of the purchaser's problem (Eq. (8c)) ensures that demand is shifted away from suppliers with high offer prices. In addition, it allows accounting for key peculiarities of agricultural markets. First, basing demand distribution decisions on baseline supply shared derived from observational data allows accounting for the fact that purchasers' prefer certain suppliers to others due to reasons which are not modeled explicitly such as bi-lateral trade agreements, historically grown trade relations, or the reliability of suppliers (Ge et al., 2021). Second, accounting in the supply shares for the deviations of suppliers' current sales from their respective baseline values allows purchasers to respond to failures of individual suppliers due to, e.g., export restrictions (d'Amour and Anderson, 2020). Third, the effective price elasticity of consumption decreases with increasing net import dependencies; the larger the magnitude of $A^*_{\mathrm{d},s}$, the larger is the share of its total exports which a country needs to balance it food imports, and the more difficult it becomes for the country to buffer price hikes at the global grain market. For the baseline state, this can be seen by first noting that the total budget $B^*_{\mathrm{d},s}$ can approximately be expressed as the baseline average purchasing cost for the considered commodity divided by $A^*_{\mathrm{d},s}$ and inserting this into Eq. (8c). For a region, where import of the considered commodity are negligible in the trade balance (i.e., in the limit $A^*_{\mathrm{d},s} \ll 1$), demand is elastic, $D_{r\leftarrow s} \sim \left(p^{(t)}_{\to s}\right)^{-\epsilon_{\mathrm{d}}}$. By contrast, the demand of a fully import dependent region ($A^*_{\mathrm{d},s} = 1$) is basically inelastic $D_{r\leftarrow s} \sim \left(p^{(t)}_{\to s}\right)^{-1}$.

4. Data processing

We split the discussion of data processing into two subsections: on data we use to initialize the model (*baseline* data) and on data we use to drive simulations (*forcing* data). In Fig. 1 we summarize the whole conceptual framework of the model, including the data flow.

4.1. Regional and temporal resolution

Agrimate is designed to have a flexible regional and temporal resolution. For the results presented below, we use 24 time steps per year, so about 15 days (roughly two weeks) per time step. Further *Agrimate* operates on a global scale, segmented into 28 regions (Fig. 2), providing a comprehensive yet streamlined perspective on agricultural trade. These regions range from aggregates of several nations – such as the North Africa region encompassing Algeria, Libya, Morocco, Sudan, Tunisia, and Western Sahara – to individual countries that stand out due to their large populations or large exporter, like the United States of America (USA), Australia, China, Argentina, and Russia. Further, we account for Egypt as the world's largest wheat importer. A full delineation of these regions and their encompassed nations is available in Suppl. Tbl. C.1.

4.2. Baseline data

To initialize the model, we derive annually-periodic baseline time series of suppliers', purchasers', and consumers' variables accounting for the seasonality of the market but not for production anomalies (baseline state). The computed key initialization data are region-level baseline values for (i) annual production $\{X^*_r\}_r$, (ii) annual domestic supply (which, for simplicity, we call consumption) $\{C^*_s\}_s$, and (iii) annual bilateral trade flows $\{X^*_{r\to s}\}_{r,s}$, which have to be self-consistent, i.e., for each region, the sum of outgoing trade flows (including the domestic flow) needs to equal the production level, and the sum of incoming trade flows needs to equal the consumption level. This allows us to generate spatially and temporally consistent trade patterns. The technical details of the initialization procedure are presented in Suppl. Sec. D.7.4.

We source our baseline data from the portal of the Food and Agriculture Organization of the United Nations (FAOSTAT) (FAO, 2022), which offers a comprehensive database on annual production, supply,

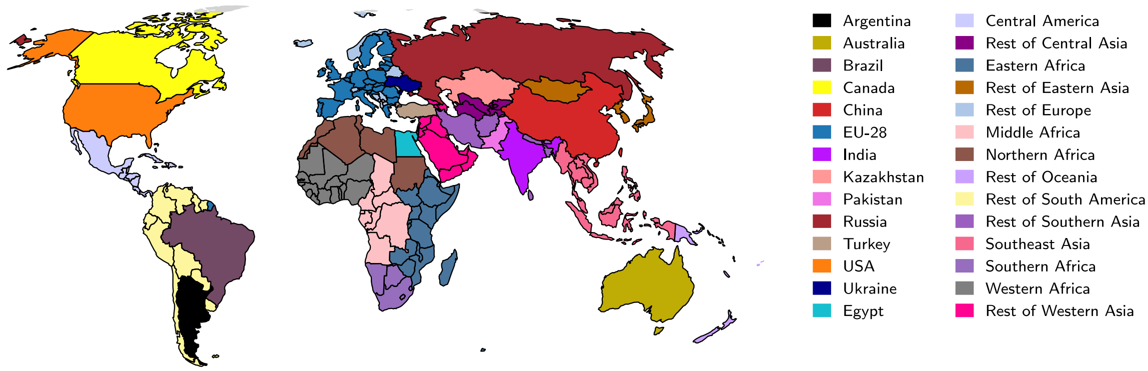

Fig. 2. Regional coverage. Map of the 28 regions and countries used in this study (cf. Suppl. Tbl. C.1 for the mapping of countries to regions).

trade, and stock variation per country and food item group (so-called food balance sheets), as well as detailed trade matrices. Even though each country-level food balance sheet is harmonized internally, they are not harmonized across countries. To this end, we have developed a harmonization procedure, in which we search for a self-consistent set of country-level import, export, and bilateral trade values matching the values reported by FAOSTAT as closely as possible (cf. Suppl. Sec. E.1). Combining these data with harvest calendars from the Center for Sustainability and the Global Environment (SAGE) (Sacks et al., 2010; SAGE, 2021) and the United States Department of Agriculture's (USDA's) Foreign Agricultural Service (USDA, 2021) datasets, allows us to estimate the harvested amounts in each time step of the harvest season. We then calculate a Nash equilibrium solution (*Nash-baseline*) for the intra-annual variations of regional production, regional consumption and regional trade under the simplifying assumptions that (i) markets clear in each time step, (ii) regional harvests do not deviate from the average of the chosen multi-year baseline period 2007–2009, and (iii) storage and sales variations are annually periodic. This *Nash-baseline* accounts for several region-specific variables, which introduce regional heterogeneity of modeled consumer-site response to price and supply shocks, such as stock-to-consumption ratios, derived from USDA's Production, Supply, and Distribution (PSD) online data on stocks and domestic consumption (USDA, 2023). Further, we estimate the baseline ratio of production and imports value over the total merchandise exports ($A^*_{d,s}$) from the FAOSTAT and World Bank (World Bank, 2022) databases, and the average shares of household expenditure on food ($A^*_{c,s}$) is derived from USDA's Economic Research Services data (USDA, 2022b) (cf. Suppl. Sec. E.2 for details).

It is important to note that assuming sales and storage levels to be annually periodic (assumption (iii)) in the *Nash-baseline* is internally consistent because the Nash equilibrium solution was derived under the assumptions that harvests do not vary from one year to the next and agents' expectations on their upcoming domestic harvest and the global harvest are perfect. This also implies that the storage levels in the *Nash-baseline* do not accumulate over multiple years. By contrast, in the dynamic model, annual stock carryover can change, allowing storage levels to vary over the years, which complies with the logic of the dynamical *Agrimate* model where agents have imperfect expectations about the domestic and foreign harvests. To this end, we use the Nash equilibrium solution only to initialize the model, and then let the model dynamically evolve to its dynamic unperturbed baseline state over a spin-up period of 4 years.

4.3. Forcing data

The model is driven by exogenous time series of (i) region-level harvest anomalies and (ii) trade restrictions.

Several steps are needed to obtain the empirical harvest anomaly data. First, for each country, we fit a trend to the production time series using a local regression method (LOWESS) (National Institute of Standards and Technology, 2024) with a fitting window of approximately 10 years. Second, we calculate relative production anomalies by dividing the fit residuals by the trend values. Third, we create synthetic time series of per-country sub-annual production by multiplying the annual anomalies by the baseline production and distributing it across the harvest season using production profiles from the initialization step. Fourth, we aggregate the per-country input production time series to the regional level (cf. Suppl. Sec. E.3 for details). Repeating the same procedure with the production data from USDA's PSD Online database (USDA, 2023), allows us to compare the production anomalies obtained with both global datasets (Suppl. Sec. B).

We use data from the Agricultural Market Information System (AMIS) (AMIS, 2021) to calibrate the trade restrictions. AMIS provides a comprehensive list of export policies implemented since 2007 with details on their timing and type of restriction. We represent export policies by attributing export restrictions $\Delta_r^{(t)}$ of 95% and 50% to countries issuing export bans and export taxes, respectively. The strength of regional export restrictions is obtained as the baseline exports weighted average of the restrictions issued by the countries in the region. We present the full table of export restrictions used to drive the model in the current application in Suppl. Tbl. E.4. We perform a sensitivity analysis to show that our results are robust under varying assumptions on the effectiveness of export taxes in reducing exports (cf. Suppl. Sec. F).

5. Results

5.1. Hindcasting setup

To test model performance, we test how well *Agrimate* can reproduce the price and trade dynamics during the global food price crises in 2007/2008 and 2010/2011. We thereby focus on wheat as the food grain that is trade most internationally (in terms of weight and energy supply) (USDA, 2023). We use the average of the 2007–2009 wheat trade network as baseline to initialize the model. We start the model computations in 2000 to give the trade dynamics enough time to spin up, and report results for the period 2006–2011.

In our analysis, we consider three scenarios: In the *baseline* scenario, the model is driven by the averaged harvests of the 2007–2009 baseline period. For the *production anomalies* scenario, we multiply the baseline production by the production anomalies of the period 2005–2011 (see Suppl. Sec. E.3 for details on the detrending method and Fig. 3a and b for global production data and production anomalies). Finally, in the *production anomalies & export restrictions* scenario used for the hindcasting, we additionally account for the historical export restrictions. For simplicity, we will in the following refer to this scenario as *full model*. Between 2007 and the end of 2011, 7 regions – Russia, Argentina, Kazakhstan, Ukraine, China, Eastern Africa, and Rest of Western Asia –

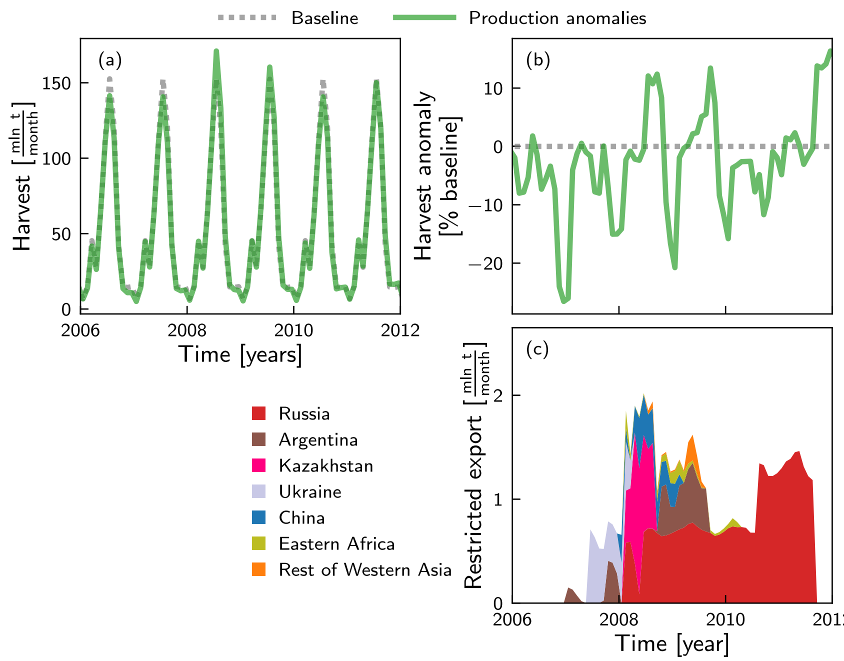

Fig. 3. Global wheat production and national export restriction. Evolution of global production (a) and production anomalies (b) over the time period 2006–2011 used for the simulation in the baseline scenario (gray dotted lines) and in the production anomalies scenario (green solid lines). c: Wheat restricted from export (in million metric tons (mln t) per month) to international markets by the historical export restriction as derived from AMIS data (AMIS, 2021).

imposed export restriction. In the model, we approximate the amount of wheat that was restricted from export to international markets as the amount of grain which these regions' suppliers expect to not be able to sale at international markets (Fig. 3c). Suppl. Tbls. D.1 and D.8 list all parameter values used in the simulations throughout the paper.

In the following two sections, we first compare our globally aggregated model results to empirical data in Section 5.2 before discussing the details of the trade dynamics at the example of the supplier–purchaser pair Russia–Egypt in Section 5.3.

5.2. Comparison to observational data

Overall, there is a good agreement between the world market prices computed by the full model and observed real (deflated) world market prices, including the price spikes during both crises. To see this, we first define the world market price index in the model as the volume weighted sum of the price indices of all international exports. We then compare this price to the real (deflated by the monthly US consumer price index) export price for US Hard Red Winter wheat (observed world market price) by multiplying the price index with the average observed world market price for the year 2006 (Fig. 4a). The price response to the harvest anomalies is non-linear, in the sense that harvest anomalies of less than 20% translate into price anomalies of more than 50%. Further, by comparing the full model with the production anomalies scenario, we see that the export restrictions have substantially driven the price during the two crises.

Also with regard to annual supply changes and stock variations, there is a reasonable correspondence between the full model and the data reported by FAO, on the global level (Fig. 4b and e) as well as – to a somewhat lesser extent – on the regional level (Fig. 4c,d,f,g). We thereby compare simulated supply anomalies relative to the 2007–2009 average (baseline) with observed anomalies with respect to the fitted supply trend (cf. Suppl. Sec. E.5) and also the stock anomalies are measured relative to these baselines. (Hence, +5% stock increase means that the stock level has increased within the given year by 5% of the typical annual supply.) On the global level, the simulation reproduces the global decline in supply and stocks in the years 2006 and 2007 which are a consequence of two consecutive global crop failures in 2006 and 2007 preceding the 2007/08 global food price crisis. For the other years, the sign of simulated global supply and stock anomalies corresponds to the reported anomalies, except for the supplies of the years 2008 and 2011 where modeled supply anomalies are negative whereas reported supply anomalies are positive. These discrepancies may arise, because we do not model consumer support policies such as guaranteed prices for stables or tax concessions on food staples, which helped keeping up consumption (and thus supplies) in times of high prices (World Bank, 2010; Demeke et al., 2008; Trego, 2011).

On the regional levels, we discuss only the anomalies for the year 2007 as the start year of the 2007/08 food crisis (Fig. 4c,d,f,g). The regional anomalies for the year 2008 are shown in Suppl. Fig. A.1. The simulated supply anomalies are largely consistent with the reported anomalies. In particular, the model reproduces the reported supply reductions in the European Union and the United Kingdom (EU-28), Canada, the USA, and Ukraine, which mainly result from weather-induced domestic production failures, reasonably well (cf. Suppl. Fig. A.2 for 2007 regional production anomalies). Further, the model also captures the resulting supply reductions in import-dependent regions (cf. Suppl. Fig. A.3) in the Middle-East and North Africa, Eastern Africa, and South-East Asia. However, it fails to capture observed supply increases in some regions of the Southern Hemisphere, such as Argentina, Western and South Africa, or Australia. With regard to stock anomalies, *Agrimate* reproduces the signs of these anomalies correctly for large parts of Latin America, North Africa, and West-, South-, and South-East Asia, including developing countries with large vulnerable low-income populations, i.e., potential hunger hot spots. Also, the large positive stock variations in regions that imposed export restrictions already in 2007 such as Argentina and Ukraine are reproduced well. However, it is important to be aware of the uncertainties inherent to the reported supply and stock data, especially on the regional level. For instance, according to USDA supply decreased in 2007 in Argentina, South Africa, or Australia in contrast to the increases reported by FAO (cf. Suppl. Sec. B). These results are fairly robust under changes of the model parameters, as discussed in Suppl. Sec. F. *Agrimate* is also able to reproduce the world market price spikes for other food staples as shown for rice, maize, and soybean in Suppl. Sec. G and Suppl. Figs. G.1 to G.3. Further, *Agrimate* also allows reproducing the world market

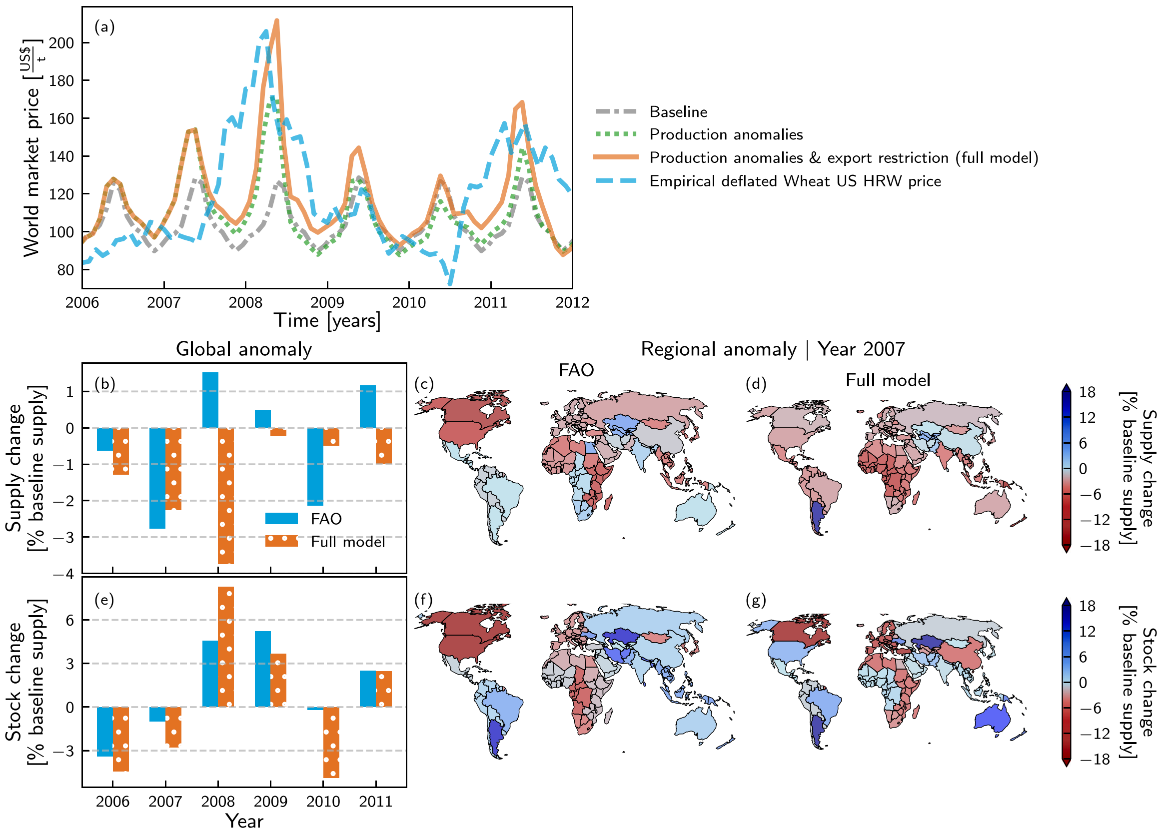

Fig. 4. Model performance on global and regional levels. a: Comparison of simulated world market prices as obtained for the unperturbed baseline scenario (gray dash-dotted line), by accounting for the historical production changes (green dotted line), and additionally for the historical export restrictions (full model, orange solid line) with historical real (i.e., deflated by US consumer price index) world market prices for US Hard Red Winter wheat (blue dashed line) for the period 2006–2011. b–g: Left panel: Comparison of globally aggregated supply (b) and stock changes (e) for the years 2006–2011 as obtained from the full model (orange dotted bars) and the respective changes in reported data from FAOSTAT (FAO, 2022). Middle and right panels: Comparison of regional supply changes (c and d) and stock changes (f and g) anomalies for the year 2007 as obtained from FAOSTAT (c and f) and the full model (d and g).

price spike for wheat observed at the onset of the full-scale Russian invasion of Ukraine in 2022 (Suppl. Fig. A.5).

5.3. Purchaser–supplier interactions

To better understand how the aggregated trade and price dynamics emerges from the interplay of the individual agents, we discuss the dynamics of the trade relation between Russia as a large exporter (Fig. 5) and Egypt (Fig. 6) as the world's biggest wheat importer, which has strong import dependencies from Russia, the USA, EU-28, and Australia (Fig. 7).

Since Russia's producer site storage holder (supplier) is a profit maximizer and storing grain is costly, it aims to completely deplete its storage content over the agricultural year (from July until June for wheat in Russia (USDA, 2022a)) before the next domestic harvest season (cf. Fig. 5a and f). To minimize the storage costs, the supplier is willing to sell at lower prices to the domestic and the international markets directly after the harvest season when its storage is comparably full, than towards the end of the agricultural year. This leads to the seasonal variation of both the domestic and international offer prices (cf. Fig. 5b and e). Thus, storage carryovers into the next local agricultural year arise only from imperfect expectations regarding its own harvests or market developments, and are comparably small. This renders the supplier prone to (close-to) stockouts. In the production anomaly scenario, such a situation arises for instance in early 2008, when after the bad global harvests of 2006 and 2007, global demand is higher than usual which drives the price at the international market, and the Russian supplier decides to sell more than usual within the agricultural year. In consequence, it cannot fulfill the demand requests of Egypt and other purchasers towards the end of Russia's agricultural year. In consequence, there is a sharp drop in Russia's international supplies (Fig. 5c and Fig. 7b) and a strong increase in the domestic and international offer prices of the Russian supplier (Fig. 5b and e).

The scenario with export restrictions (cf. Fig. 5d) reveals that these dampen the domestic price even below the baseline level; since the supplier can sell less at international markets, it is willing to sell at lower-than-usual prices domestically (Fig. 5b). This indicates that export restrictions may indeed allow to increase food security domestically. However, the price-driven increase in domestic demand cannot compensate for the lost export opportunities. In consequence, overall supplies (domestic + international) (Fig. 5c) are lower than in the baseline scenario, and the supplier storage starts to fill up (Fig. 5f). Thus, the domestic export restrictions smooth Russia's supplies over the year and reducing the risk of (close-to) stock-outs towards the end of the local agricultural year (cf. Fig. 7b and c).

However, for consumers in import-dependent Egypt the export bans – especially those issued by Russia – have adverse consequences. While in normal times about 28% of Egypt's imports originate from Russia (Fig. 7 d and e), from early 2008 onward, Egypt's strategic storage holder (purchaser) has to replace about half, and from late 2010 till late 2011 even 95%, of the Russian imports (Fig. 7f). By shifting more of its demand to other (unrestricted) suppliers, mainly the USA and EU-28, it effectively mitigates the Russian supply failures, so that purchases partially recover within a few months after Russia first issues export restrictions in early 2008 (Fig. 6e). However, for most of the time when Russia (and Kazakhstan) restrict exports, the demand of the Egyptian purchaser is higher than in both the baseline and the production anomalies scenarios while the amount of grain it actually purchases

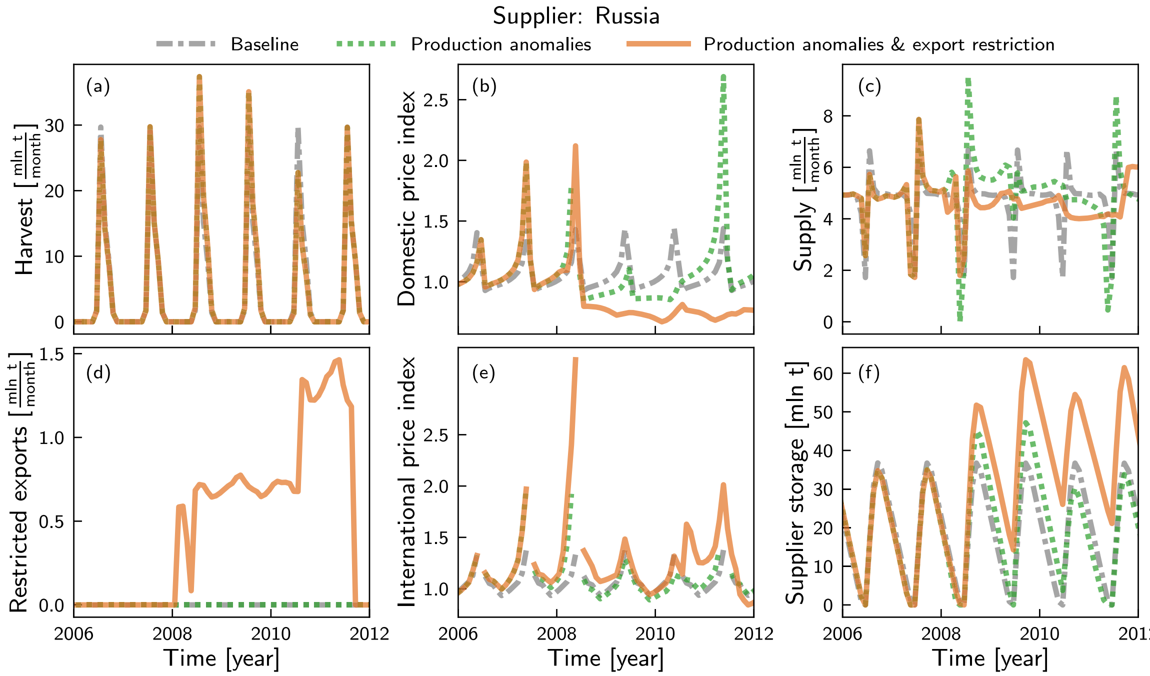

Fig. 5. Supplier dynamics for Russia. Simulated monthly time series of harvest (a), domestic price index (b), sales (c), restricted exports (d), international price index (e), and commercial (supply-site) storage (f) of Russia for the unperturbed baseline scenario (gray dash-dotted lines) as well as for the scenarios accounting for historical production anomalies (green dotted lines) and, additionally, for the historical export restriction (full model, orange solid lines). Harvest, restricted exports, supply, and storage are given in million metric tons (mln t).

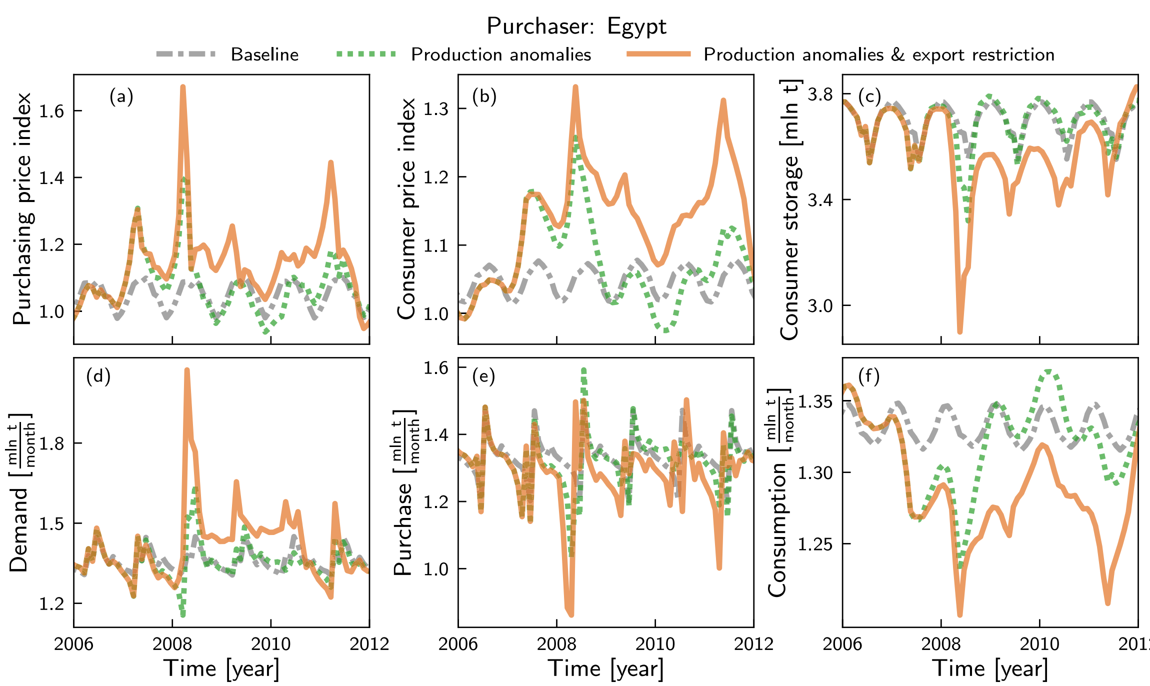

Fig. 6. Purchaser dynamics for Egypt. Simulated monthly time series of purchasing price index (a), consumer price index (b) as well as consumer storage (c), demand (d), purchases (e), and consumption (f) (all in million metrics tons (mln t)) of Egypt for the unperturbed baseline scenario (gray dash-dotted lines) as well as for the scenarios accounting for historical production anomalies (green dotted lines) and, additionally, for the historical export restriction (full model, orange solid lines).

is lower. This shows that some of its demand requests are unsuccessful, except, toward the end of the export restriction period (in late 2011), when the Egyptian purchaser manages to buy unusually high amounts of wheat from the Rest of Western Asia region which is dominated by Syria. In consequence, Egypt has to refer to its strategic storage to fulfill its domestic demand much stronger than in the scenarios without export restrictions (Fig. 6c).

Further, the export restrictions raise the price, at which Egypt can purchase grain at the international market, compared to the baseline and production anomalies scenarios (Fig. 6b). The substantial price spikes at the international market are damped by the strategic storage so that Egypt's consumer prices lag the international market price and are more stable; hikes of the consumer price are about 25% smaller than the corresponding hikes of the international price (Fig. 6a and

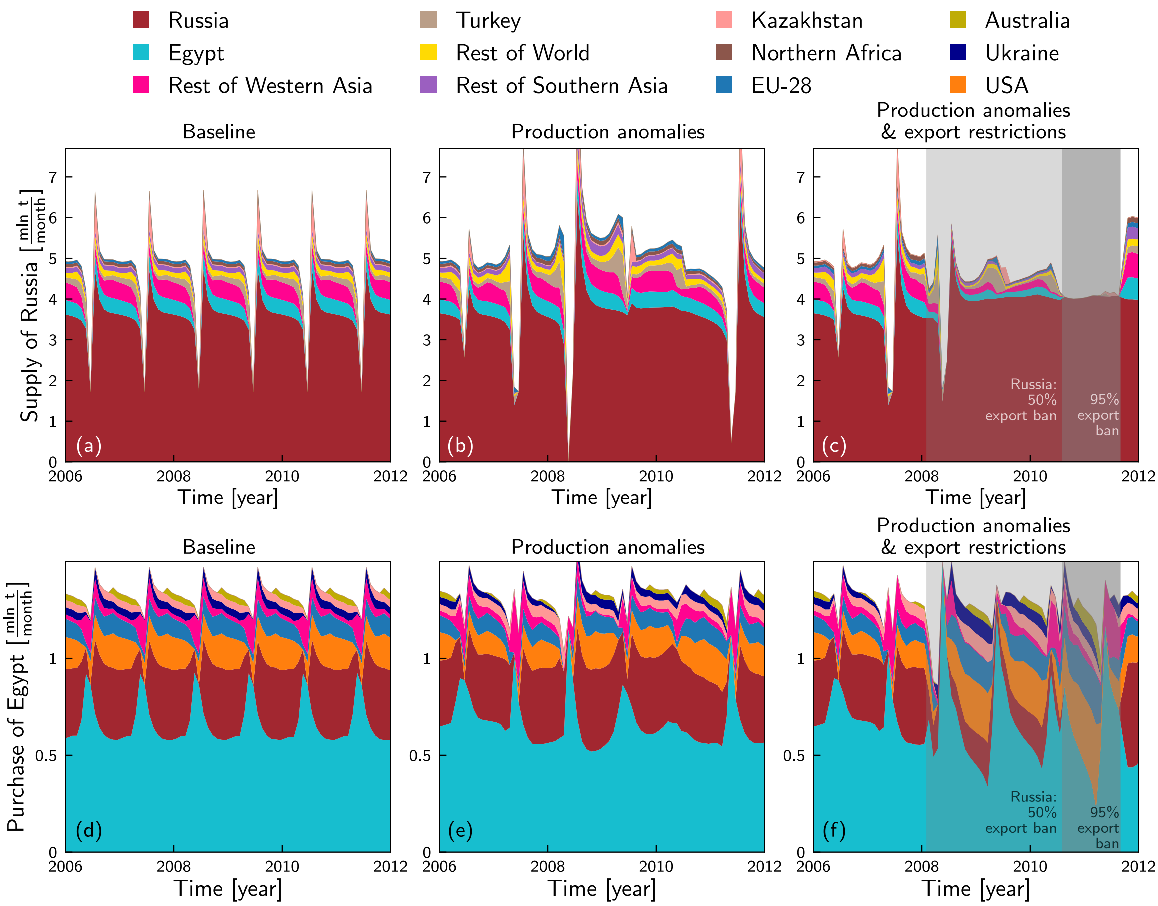

Fig. 7. Adjustments of trade between Russia and Egypt in response to supply failures. Simulated monthly time series of Russian supplies (a–c) and Egyptian purchases (d–f) (both in million metric tons (mln t)) for the unperturbed baseline scenario (left column), for the scenarios accounting for production anomalies (middle column), and additionally for export restrictions (full model, right column). Color code denotes purchasers of Russian supplies (a–c) and suppliers of Egyptian purchases (d–f). Light and dark gray shaded areas in c and f indicate time periods where Russia imposed partial (50%) and full (95%) export restrictions, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

b). Nevertheless, consumption is lower than in the scenarios without export restriction, indicating that the export restrictions increase the food security risks for consumers in Egypt.

5.4. *Relative importance of production failures and export restrictions as price drivers*

The example of the supplier–purchaser pair Russia–Egypt illustrates how export restrictions reduce food security risks in the countries that issue them, but jeopardize food security in import-dependent countries. This observation remains valid on the global level. To see this, we first analyze domestic supply, consumption, and stock changes for key exporting and importing regions in the year 2008 (Fig. 8), the year with the most severe export restrictions (cf. Fig. 3c). In the scenario accounting for production anomalies only (blue bars) (Fig. 8c), Ukraine suffer consumption losses and the stocks of Argentina and Kazakhstan decline substantially (Fig. 8e). When additionally accounting for the export restrictions raised by all four countries (orange dotted bars), the decline in stocks is reduced for Argentina and Kazakhstan to nearly zero, while consumption losses change into gains in Ukraine, and the consumptions of Russia, Kazakhstan, and Argentina increase as well. By contrast, for import-depending countries (Fig. 8, right column), domestic supply and consumption are already reduced in the production anomaly scenario (except for Rest of Central Asia), and export restrictions further aggravate these losses (Fig. 8b and d). Further, under export restrictions, some regions like Egypt or Southeast Asia have to tap into their reserves (Fig. 8f).

In the two analyzed crises, production failures and export restrictions have both strongly driven the hikes of annual world market prices (Fig. 9). In 2007, the year with the strongest global production failures (Fig. 3a), prices were driven much stronger by these production failures +13.7 US\$/t (+13.2%) compared to the baseline scenario than by the export restrictions +16.7 US\$/t (+16.2%) which the first countries just started to issue in the second half of 2007 (Fig. 3c). In 2008, the share of restricted international exports increased with the number of countries issuing export restrictions. These raised the world market price in 2008 to a similar extent as the production failures, which were smaller than in 2007. Combined both drivers increased the price by +23.3 US\$/t (+22.5%), the strongest increase in all considered crisis years. In the 2010/2011 crisis, production failures were less severe than in 2007/08, and the observed price hike was mainly driven by the export restrictions raising the price by +5.6% and +12.3% in 2010 and 2011, respectively.

5.5. *Food security risks arising from multi-breadbasket failures in the historical climate and in a +2 °C world*

In the previous section, we showed that the global food systems is susceptible to production failures and export restrictions. Notably, in 2007, simultaneous harvest failures in several main producing regions resulted in a decrease of the global wheat production by approximately 5%. We further showed that this production decrease was a main driver of the price peak in 2007 (Fig. 9), underscoring the potential of multi-breadbasket failures to impair food security, globally.

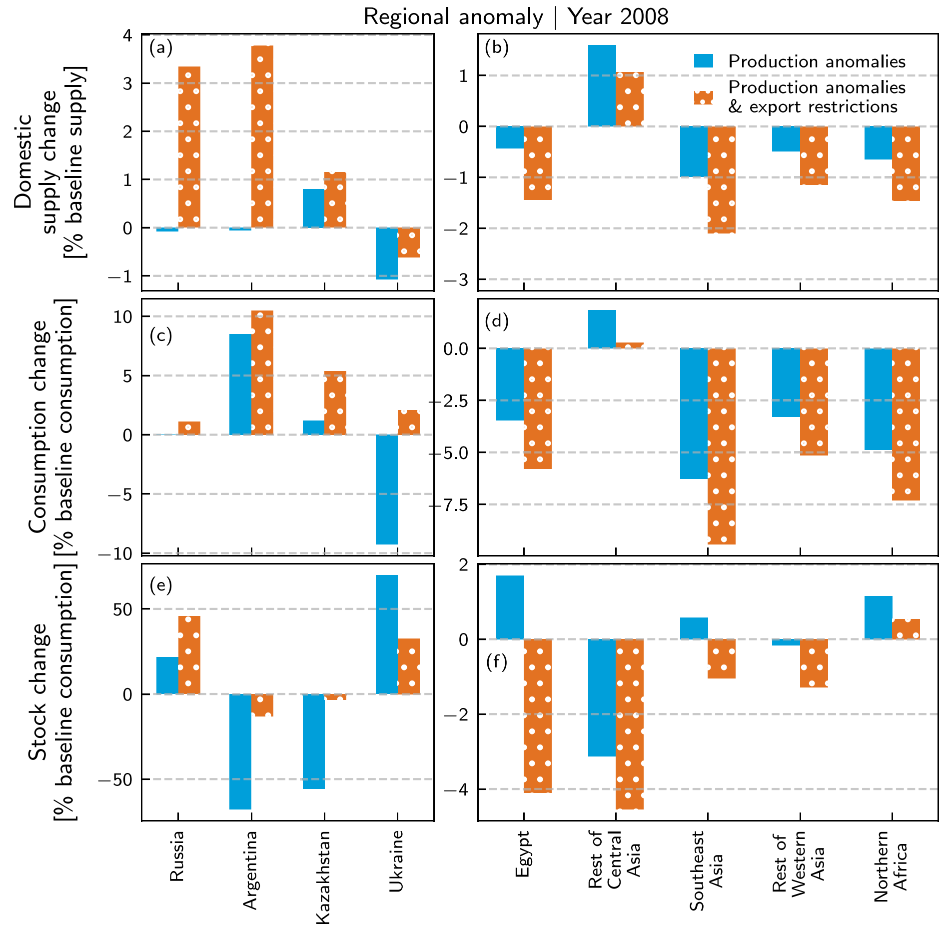

Fig. 8. Trade impact of global production failures and export restrictions. Simulated regional changes in domestic supplies (a and b), consumptions (c and d) and stocks (e and f) for the year 2008 in the scenarios accounting for global production anomalies (blue bars) and additionally for export restrictions (full model, orange dotted bars) relative to the unperturbed baseline scenario. Left and right columns show the resulting changes for net exporting regions that issued export restrictions and net importing regions, respectively.

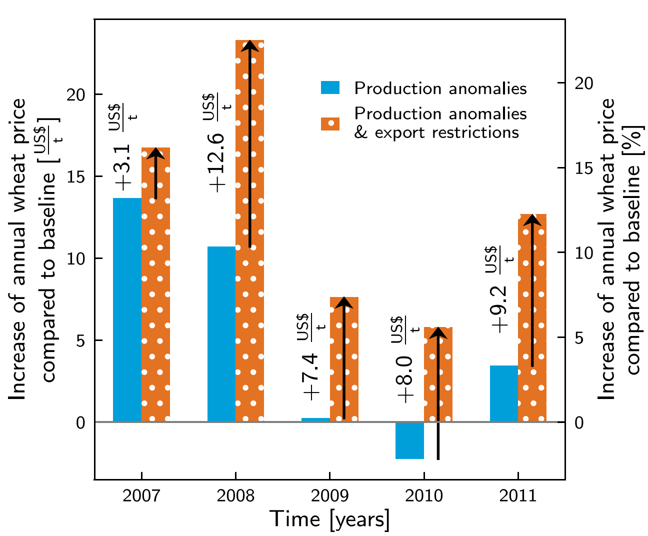

Fig. 9. Contributions of global production failures and export restrictions to world market price hikes during the 2007/08 and 2010/11 crises. Simulated absolute and relative annual world market price changes ((in US$ per metric ton and %, respectively) in the scenarios accounting for production anomalies (blue bars) and additionally for export restrictions (full model, orange dotted bars) compared to the baseline scenario. Black numbers indicate absolute price changes in the full model compared to the scenario with production anomalies.

We next assess potential food security risks that may arise from the projected increase in the likelihood of multi-breadbasket failures under ongoing global warming (Gaupp et al., 2019). Using climate data from the "Half a degree Additional warming, Prognosis and Projected Impacts" (HAPPI) experiment (Mitchell et al., 2017) and employing regular vine copulas, Gaupp et al. (2019) modeled the spatial correlations of adverse weather conditions in the five breadbasket regions Argentina, Australia, China, India, and the USA. This approach enabled them to analyze how spatially correlated adverse weather conditions could increase the likelihood of (multi-)breadbasket failures at +1.5°C and +2 °C of global warming (with regard to preindustrial levels) compared to the historical climate conditions of the period 2006–2015. For wheat, Gaupp et al. (2019) found that the likelihood of multi-breadbasket failures increases substantially in a +2 °C world; the return period of simultaneous harvest failures in all five breadbasket regions reduces from 43 years under historical climate conditions to 15 years in a +2 °C world, indicating a substantial increase in climate risks to global food security.

From the analysis of Gaupp et al. (2019)), we first derive the probabilities of zero to five of these breadbasket failing for wheat under historical climate conditions and in a +2 °C world (Table 1). Second, for each of the breadbaskets, we derive the four largest annual production failures (relative to detrended regional productions; cf. Section 4.3) over the period 2000–2020 from the FAOSTAT database (FAO, 2022), yielding production failures of 47.5%, 40%, 36.8%, 35.1% for Argentina, 56.1%, 54.7%, 43.4%, 30.3% for Australia, 18.8%, 14.8%, 14%, 10.9% for China, 8.7%, 8.7%, 8.6%, 7.9% for India, and 27.2%, 16.1%, 12.3%, 10% for the USA, respectively (Suppl. Fig. A.6).

Table 1
Probability of (multi-)breadbasket failures under the historical climate conditions of the period 2006–2015 and in a +2 °C world. Probability distributions of multi-breadbasket failures for the five regions – Argentina, Australia, China, India, USA – considered by Gaupp et al. (2019) as obtained for the historical climate conditions of the period 2006–2015 and at +2 °C of global mean temperature warming compared to preindustrial levels (+2 °C world).

	Number of breadbasket failures					
	0	1	2	3	4	5
Historical (2006–2015) climate conditions	4.5%	17%	29.9%	30.9%	15.4%	2.4%
+2 °C world	0%	0.6%	9%	51.6%	32.2%	6.6%

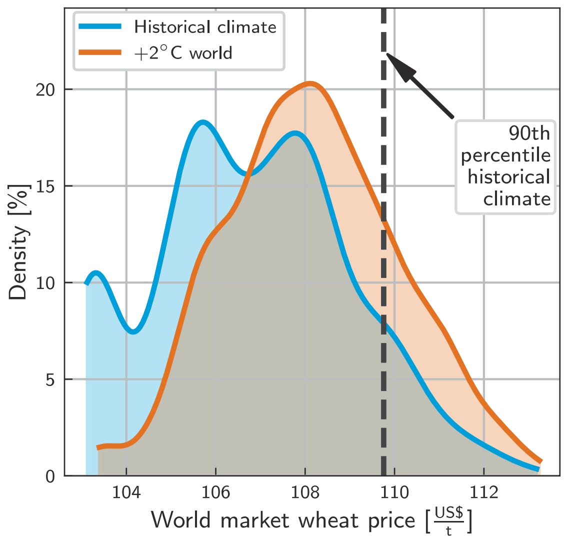

Fig. 10. Distribution of world market price responses to (multi-)breadbasket failures under historical climatic conditions and in a +2 °C world. Distribution of simulated two-year-averaged world market price responses to (multi-)breadbasket failures, as obtained for the historical climate conditions of the period 2006–2015 (Historical climate, blue) and at +2 °C of global mean temperature warming compared to preindustrial levels (+2 °C world, orange). The black dashed line depicts the 90th percentile of the historical distribution. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Third, we derive 1000 production shock scenarios for the historical climate conditions and in a +2 °C world by randomly drawing failure combinations from the distributions of multi-breadbasket failures (Table 1). For instance, for the historical climate conditions, we generate 299 (29,9%) out of the 1000 shock scenarios with two simultaneous production failures, which could, for instance, include the combination of a 47.5% failure in Argentina and a 16.1% failure in the USA (or a 10.9% failure in China and a 8.6% failure in India). These 1000 shock scenarios per warming level are then employed to drive *Agrimate* in order to assess how (multi-)breadbasket failures and their increased likelihood under global warming could affect price and trade dynamics.

In our scenario setup, the breadbasket failures occur during one calendar year. However, to account for differences in the harvest seasons across regions as well as inter-annual trade dynamics, such as storage movements and lagged shifts in demand, we consider the year of the harvest failure (year one) as well as the subsequent year (year two) in our analysis. Consequently, all the results presented in this section are two-year aggregates.

As shown by Gaupp et al. (2019), the probabilities that none or just one of the breadbaskets perceives a production failure sharply decreases to almost zero in the +2 °C scenario (Table 1), while multi-breadbasket failures become more likely. This results in a substantial change in the distribution of the world market price responses (Fig. 10). In a +2 °C world, the price response (shown in orange in Fig. 10) is centered at a higher price level and has a thicker high-price shoulder than the price distribution obtained under the historical climate conditions (shown in blue in Fig. 10).

Further, the risk of critical, 90th percentile price spikes under the historical climate conditions (black dashed line in Fig. 10) more than doubles.

Since regional purchasers and consumers are budget constraint, rising world market prices lead to reductions in consumption. Thus, under each scenario with at least one breadbasket failure, the regional consumption decreases relative to the unperturbed baseline scenario under the historical climate conditions as well as in a +2 °C world, as shown exemplarily for Western Africa in Fig. 11a. Further, the risk of severe consumption losses (*consumption risk*), defined as 90th percentile consumption loss events under historical climatic conditions (black dashed line in Fig. 11a) is amplified in a +2 °C world compared to historical climate conditions in all regions, with strong regional heterogeneities (Fig. 11b). On the one hand, in the USA or Australia the consumptions risk under historical climate conditions is moderate (2.6% and 1.2% compared to baseline consumption, respectively), and the risk amplification is comparably small (<31%). Also in the EU-28, the consumption risk under historical climate conditions is small (<0.25% relative to baseline consumption) but doubles in a +2 °C world (108%). On the other hand, regions in Africa, South and Southeast Asia, and South America have a moderate to elevated consumption risk (1%–6%) under historical climate conditions, which is substantially amplified in a +2 °C world, with Brazil showing the highest risk amplification (130%). The main reason for this strong risk amplification is that Brazil heavily relies on only three wheat importers, and two of them – Argentina and the USA – are directly affected by the breadbasket failures.

The increased likelihood of multi-breadbasket failures in a +2 °C world leads to either increasing or decreasing export quantities compared to historical climate conditions, depending upon the considered region (Fig. 11c). Directly affected regions, particularly Australia and Argentina, perceive the largest export quantity losses. The resulting supply failures are mitigated by additional exports of other not directly affected producers, such as Brazil and Turkey. Notably, also these not directly affected regions, face substantial amplifications in consumption risk in a +2 °C world compared to historical climate conditions. This could incentivize these countries to raise export restrictions to avoid domestic price increases due to competition between the domestic and international markets, which could further drive world market prices. However, analyzing such potential dynamics would go beyond the scope of the paper and is therefore left for future work.

Noteworthy, in all regions, the increased risk of price spikes in a +2 °C world results in an increase in regional export revenues compared to the historical climate conditions (Fig. 11c). Even countries experiencing a decrease in export quantities increase their export values, which is particularly striking for Argentina, Australia, and the USA. In conclusion, our results indicate that, while consumers in all regions are exposed to higher risk of consumption losses in a +2 °C world compared to historical climate conditions, suppliers gain through higher export revenues (cf. Suppl. Figs. A.7 to A.34 for details).

6. Discussion

We have introduced the new agent-based model *Agrimate* designed to resolve the intra-seasonal dynamics of international agricultural markets and resulting risks to global and regional food security. Having

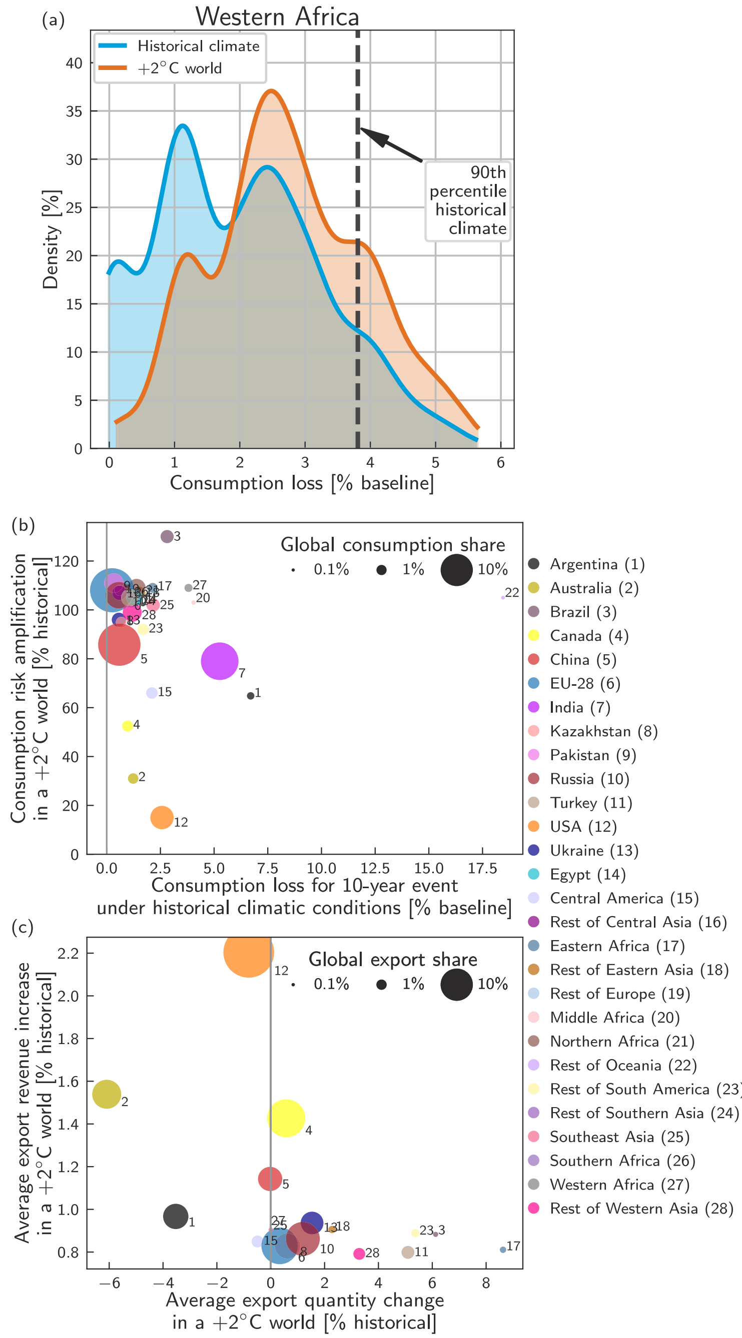

Fig. 11. Consumption loss and changes in exports caused by (multi-)breadbasket failures under historical climatic conditions and in a +2 °C world. (a) Distribution of simulated two-year consumption losses due to (multi-)breadbasket failures in Western Africa, as obtained for the historical climate conditions of the period 2006–2015 (Historical climate, blue) and at +2 °C of global mean temperature warming compared to preindustrial levels (+2 °C world, orange). The 90th percentile of consumption losses relative to baseline defines the regional consumption risk (black dashed line). (b) Consumption risk amplification of a 90th percentile event in a +2 °C world (relative to historical climate conditions) over the regional consumption risk under historical climate conditions (relative to unperturbed baseline state) for each region (colored circles and numbers). (c) Average two-year export revenue increase over average two-year export quantity change in a +2 °C world relative to historical climate conditions for each region (colored circles and numbers). The sizes of the circles in (b) and (c) represent the regional share on global wheat consumption and export, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

a high temporal (bi-weekly) resolution and accounting for the topography of the trade network, *Agrimate* allows resolving the response of stock- and consumption levels to short-term, weather-, conflict-, or trade policy-induced supply failures which remain hidden by established agricultural market modeling approaches due to their coarser (annual to decadal) resolution.

The model allows us to gain a detailed understanding on how the market dynamics emerges from the interactions of the individual agents (Figs. 5–7). A feature distinguishing our model from the majority of agroeconomic market models, as for instance the scholarly competitive storage model (Williams and Wright, 1991), is the relaxation of the market clearing assumption. While it has been shown that this assumption can be justified at annual or multiannual time scales (Schewe et al., 2017), there is solid evidence for out-of-equilibrium market dynamics in crisis situations (Tadesse et al., 2014; Lagi et al., 2015; Pichler et al., 2022; Du et al., 2011). Especially, it is important to resolve out-of-equilibrium dynamics to describe market responses to uncoordinated policy measures such as export restrictions, which come as a surprise for the other market participants and can lead to rationing and supply–demand mismatches (Giordani et al., 2016; Sun et al., 2021). Except for cobweb like models (Lundberg et al., 2015) – which however do not allow for the quantitative reproduction of the price and trade dynamics at agricultural market (Mitra and Boussard, 2012) – out-of-equilibrium dynamics cannot be captured by most established modeling approaches.

In *Agrimate*, the supply decisions of the commercial producer-site storage agents (suppliers) are based on the profit maximization principle in accordance with the competitive storage model, since this approach allows capturing the seasonality of price and trade patterns (Figs. 4a and 7). However, following the logic that incomplete market information is an important mechanism to understand the dynamics in times of crisis, the suppliers in *Agrimate* form bounded rational expectations upon the supply decisions of their competitors and the development of demand within their foresight horizon, which they update in each time step according to their gain in information. We would consider this behavior more realistic than the standard approach assuming rational expectations. For instance, the global food insecurities triggered by the Russian invasion of Ukraine, which was likely not foreseen by most market participants (Glauben et al., 2022; Lin et al., 2023).

Further, by contrast to most other modeling approaches, *Agrimate* accounts for strategic (food security) stocks in addition to commercial stocks. This modeling choice is motivated by empirical evidence that the size of reserves is an important proxy for the transmissibility of volatility from international prices to domestic consumer prices which is an important indicator for regional food insecurities; the larger the stocks, the stronger the domestic consumer price can be insulated from price volatility at international markets (Kalkuhl, 2016). Since the stock-to-consumption ratios that countries consider as the optimal trade-off between higher food security in times of crises and lower storage costs in normal times can be derived from observational data, modeling food security stocks explicitly allows us to account for regional differences in stockholding policies and thus price transmitivities.

The vulnerability of countries to trade-related food insecurities does not only depend upon (i) their import dependencies, but also upon (ii) their ability to buy grain at international markets at high prices in times of crisis (Bertassello et al., 2023). Many models account for import dependencies (Suppl. Fig. A.3) by considering the topography of the trade network (d'Amour et al., 2016; Puma et al., 2015; Ge et al., 2021). The explicit modeling of strategic stocks in *Agrimate* additionally allows accounting for the heterogeneity among countries in their ability to buy grain in crisis situations, since the price elasticity of demand depends upon the ratio of the expenses of grain imports to total exports (Suppl. Fig. A.4). Capturing both vulnerability drivers is an important prerequisite to identify countries with high food security risks in crisis situations (WFP and FAO, 2023).[1]

To test the validity of our modeling approach, we have applied *Agrimate* to the international wheat market. Hindcasting the market dynamics during the 2007/08 crisis and the 2010/11 crisis, we showed that *Agrimate* is able to quantitatively reproduce trade and world market price dynamics in crisis situations. At annual resolution, there are reported data available to which we could compare the model results. This comparison showed that *Agrimate* is able to reproduce the heterogeneous impacts of production failures and export restrictions on regional supplies and reserves rather well, given the uncertainties inherent in the underlying reported data (cf. Suppl. Sec. B). Also, with regard to consumption changes, the model provides meaningful results. For instance, among all considered regions, *Agrimate* obtains the large consumption losses in those regions where actually food riots and civil unrest sparkled during the two crisis (Worldbank, 2024).

However, in the current version, we do not account for consumer support policies such as bread subsidies (World Bank, 2010), and we do not differentiate between different groups of consumers as for instance income groups, urban and rural consumers, or feed and food use of wheat. Therefore, we would not expect the model to reproduce regional consumption responses as good as regional supply changes. Further, the current version of *Agrimate* describes an individual agricultural commodity market and does not account for cross-commodity substitution. For grains that are predominantly used for food such as wheat this may be an acceptable assumption, because consumers do not rapidly change their eating habits, and, in consequence, demand is comparably inelastic (i.e., substitution effects are small) even in crisis situations (Headey, 2011; Gebeltová et al., 2023). Finally, in our calculations, we account only for unprocessed grains and, thus, neglect re-exports from processed goods, e.g., wheat flour. This could be included in future versions of the model by coupling it to whole-economy supply chain models such as *Acclimate* (Otto et al., 2017).

We were able to show that the model allows reproducing world market prices, including the price spikes in times of crisis, at a high (bi-weekly) resolution (Fig. 4) and is therefore well suited to assess the relative importance of weather-driven (multi-)breadbasket failures and escalating export restrictions as price drivers during the two considered crises. Our modeling suggests that both drivers were comparably strong. While in 2007/08, prices were more strongly driven by production failures than by export restrictions, in 2009–2011 export restriction were the dominant short-term price driver. The upside of these findings is that cascading export restrictions may be easier to avoid than weather- or conflict-induced production failures. In this regard, our results stress the importance of international collaboration. Export restrictions are not forbidden by World Trade Organization legislation if they are issued to protect domestic food security. At the same time, our modeling shows how damaging the implications of export restrictions are for import dependent countries, in line with the literature (Deuss, 2017; Espitia et al., 2020). Therefore, international collaboration is one of the key means to help reduce market uncertainties and reduce inequality in the access to food (Farley et al., 2015) and maintain stable global food prices (Kuhla et al., 2024). For instance, it has likely contributed to avoid escalating export restriction during the COVID-19 pandemic (Fontan-Sers and Mughal, 2023) and mitigated the food security crisis triggered by the Russian invasion of Ukraine (Glauber and Laborde Debucquet, 2023; Kuhla et al., 2024).

Finally, we used *Agrimate* to assess food security risks due to multi-breadbasket failures under the historical climate conditions of the period 2006–2015 and in a +2 °C degree world. We found that the increased likelihood of multi-breadbasket failures in a +2 °C world leads to an increase in the risk of severe world market price spikes. While suppliers benefit from higher export revenues, the risk for severe consumption reductions increases in all regions jeopardizing food security, predominantly in vulnerable import dependent African and Asian countries with large low-income populations.

Our analysis on the food security risks induced by multi-breadbasket failures subject to several limitations. On the one hand, we consider harvest failures in only the five breadbasket regions studied by Gaupp et al. (2019). To this end, we might underestimate food security risks by excluding potential crop failures in other cropping regions coinciding with the failures in the considered breadbaskets. On the other hand, better-than-usual harvests in other regions could also partially offset the breadbasket failures and thus reduce food security risks. Further, we only consider a +2 °C world corresponding to strong international climate mitigation efforts. At higher levels of warming, larger food security risks may arise from even more widespread harvest failures (Kornhuber et al., 2023). Additionally, the estimates from Gaupp et al. (2019) are based on historical observations of crop failures, which are then translated to a +2 °C world based on projections by global

[1] Notably, the price elasticity of demand is different from the price elasticity of consumption. The latter depends upon the share of their income which consumers have to spend on food items, and is accounted for in many models.

climate models. This approach, does not allow accounting for potential mitigating factors such as yield increases due to technical change and CO_2 fertilization but also not for potential drivers of food security risks such as soil degradation, water scarcity, population growth and dietary changes (Gerten et al., 2020). These limitations highlight the need for more comprehensive assessments of the combined long- and short-term risks to food security arising from climate-change and socioeconomic pressures.

7. Conclusions and outlook

In the beginning of 2022, global food security was jeopardized by the largely unforeseen full-scale Russian invasion of Ukraine. The resulting disruptions of Ukrainian exports of food staples triggered widespread food insecurities, mostly in import-dependent low- and middle-income countries in the Middle East, Africa and South-East Asia (Glauber and Laborde Debucquet, 2023). In 2024, there may be another crisis at the horizon, triggered by the conflicts in the Middle East. Food transport costs have already started to rise because after several attacks on cargo ships in the Read Sea, many cargo companies decided to accept long detours (Glauber and Mamun, 2024).

To be able to broker a coordinated and thoughtful international response, rapid assessments of developing crises are needed to provide stakeholders and policymakers with critical information and decision support upon the advantages and disadvantages of the different response options (Schneider et al., 2023; Hasegawa et al., 2021; Chavez et al., 2015). *Agrimate* could be an important tool helping to build up the required capacities for integrated, quantitative in-situ modeling of systemic risks to food security.

Our analysis on multi-breadbasket failures highlights that climate-related risk to food security may increase substantially under ongoing global warming. These short term risks could be amplified by long-term drivers of food insecurities such as populations growths and changing diets, rendering especially African and Asian countries even more dependent upon food imports (Pradhan et al., 2014). Global trade is widely acknowledged as an effective means to mitigate these risks (Janssens et al., 2020). Thus, from a modeling perspective, it appears promising to couple *Agrimate* with an established agricultural integrated assessment model such as *MAgPIE* (Dietrich et al., 2019, 2022) or *GLOBIOM* (Havlík et al., 2018; IIASA, 2018) designed to assess long-term risks to food security due to production and demand changes under climate change and socioeconomic development. Such a coupled modeling framework would allow for an integrated assessment of both long- and short-term risks to food security along sustainable transformation pathways in line with the Sustainable Development Goals (United Nations Department of Economic and Social Affairs, 2024).

CRediT authorship contribution statement

Kilian Kuhla: Writing – review & editing, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Patryk Kubiczek:** Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Christian Otto:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Formal analysis, Conceptualization.

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Code and data availability

The repository containing the *Agrimate* implementation in the programming language Julia is publicly available under 10.5281/zenodo.14022004. The current model repository is available at https://gitlab.pik-potsdam.de/agrimate/agrimate/-/tree/equal-sales-penalty. The main raw output data for the hindcasting exercise and the multibreadbasket analysis as well as the sensitivity analysis is archived under 10.5281/zenodo.14870541.

Declaration of generative AI in scientific writing

During the preparation of this work, the authors used ChatGPT in order to improve language and readability during the writing process. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ecolecon.2025.108546.

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