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# The Crucial Role of Domestic and International Market-Mediated Adaptation to Climate Change

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## Abstract

Climate change effects on agricultural yields will be uneven over the world. A few countries, mostly in high latitudes, may experience gains, while most will see average yield decrease. This paper aims to quantify the role of market-mediated adjustments in attenuating the effects of climate change by allowing the expression of the new climate-induced pattern of comparative advantages within and between countries. To do this, we develop a quantitative general equilibrium trade model where the representation of land use choice is inspired from modern Ricardian trade models. We use spatially explicit information from the agronomic literature about potential yields before and after climate change for calibration and counterfactual simulations. The results show that the climate-induced yield changes generate large price movements that incentivize adjustments in production and trade. Both production and trade adjustments contribute to reducing welfare losses globally, with production adjustments making the larger contribution.

Keywords: adaptation, agriculture, climate change, international trade, land use.

*JEL classification:* D58, F18, Q17, Q54, R14.

# 1 Introduction

Climate change will widely impact agriculture, but this impact may be very different between countries. Northern countries with currently cold temperatures and short growing seasons may benefit from higher yields in some crops, while tropical countries may see reduced yields because of extreme temperatures (see table 1 for the extent of region- and crop-specific variations). These differential changes in crop productivity correspond to changes in comparative advantages both within and between countries, which could induce large relative price changes and subsequent adjustments in production and trade patterns. Therefore, one could expect a large role of market-mediated adjustments in mitigating the negative effects of climate change.

Table 1: Climate change impacts on crop yields, accounting for carbon dioxide fertilization (percentage change)

| Region | Maize | Rice | Wheat | Other crops | All crops |
|---|---|---|---|---|---|
| Asia | 15.5 | 3.9 | −53.0 | −12.8 | −8.8 |
| Commonwealth of Independent States | −9.3 | | −1.2 | −2.7 | −2.8 |
| Europe | −14.4 | 51.5 | −7.9 | −11.2 | −10.7 |
| Latin America | 3.6 | −35.7 | −33.3 | −38.0 | −34.5 |
| Middle East and North Africa | 94.1 | −87.2 | −26.9 | −30.2 | −26.0 |
| Northern America | −15.8 | 9.1 | −5.6 | −18.0 | −16.1 |
| Oceania | 15.8 | −32.5 | −40.1 | −17.7 | −20.9 |
| Sub-Saharan Africa | −0.9 | −14.7 | −76.7 | −43.9 | −39.8 |
| World | 2.1 | 3.1 | −33.1 | −17.2 | −13.2 |

Source: GAEZ project (IIASA/FAO, 2012), aggregated by crop and region based on the land rents generated by each crop in each pixel (see sections 2 and 3 for details).

The objective of this paper is to quantify the contribution of two market-mediated adjustments, changes in crop production choices and in international trade flows, to adaptation to climate change in agriculture. Meeting this objective requires a theoretical framework that integrates demand and supply for agricultural products at the global level in a consistent way. This framework is a general equilibrium trade model with a focus on the agricultural sector. The model builds on recent developments in the trade literature on assignment models (Costinot and Vogel, 2015) that have been extended to agricultural settings in Costinot et al. (2016, hereafter CDS) and Sotelo (2020). It uses gridded information from crop science on potential yields under the current climate and under climate change for calibration and counterfactual simulations. Each margin of adjustment is parameterized separately in the model. On the demand side, the parameters are the price elasticity of total agricultural demand and the elasticities of substitution between agricultural products for food and feed demand. On the supply side, the parameters are the area elasticity and the yield elasticity (in sensitivity analysis). Finally, the trade elasticity governs the flexibility to adjust between demand and supply. We rely on the vast literature devoted to the estimation of supply and demand elasticities to propose a realistic calibration for the model and to assess the uncertainty around these parameters for the sensitivity analysis.

Our model framework builds on the model recently developed by CDS. Most of the modeling choices have been made to ensure that all the behavioral parameters in the model have clear counterparts in the econometrics literature. Our model framework presents the following elements. Three types of goods are represented: crops, livestock, and a non-agricultural product. Though our modeling of livestock is very simple, the inclusion of livestock is crucial for the question at hand through its use of pastures, the single largest use of land. The model aims to represent all crops with a significant role in final demand and agricultural land use and thus includes 35 crops. Representing livestock and almost all crops allows us, on the demand side, to make a clear connection with the literature estimating elasticities for agricultural products (Comin et al., forthcoming), and on the supply side, to make sure that the opportunity costs of converting land between its various agricultural uses are accounted for. All goods are considered as imperfectly substitutable based on their countries of origin, and trade is subject to iceberg trade costs. Our modeling of crop choice builds on CDS' approach, itself inspired from Eaton and Kortum's (2002) modeling of trade in homogeneous goods (a crop choice modeling also recently used in Sotelo, 2020). Its key element is the assumption that potential yields follow an extreme value distribution, which delivers a simple expression of acreage choice, the area planted with a crop. We do not consider the possibility of extending agricultural land over forest or over protected areas, contrary to CDS, because this would require an explicit modeling of the changes caused by climate change in non-agricultural sectors such as forestry and urban sectors, a difficult endeavor, especially in a static framework (see Scott, 2014, for an example of a dynamic modeling of land-use extension). It would also require a proper accounting of the country-specific regulations related to land-use changes (Azevedo et al., 2017). However, given that we represent pastures and almost all crops, we account for the bulk of the likely counterfactual land use changes.

Using this model, we can assess the role of market-mediated adaptation to climate change. Some adaptation mechanisms have been studied extensively in the climate change literature. For example, crop scientists have proved the adaptive role of changing varieties or planting times (Challinor et al., 2014). Following Mendelsohn et al. (1994), economists using the Ricardian approach have emphasized the role of within-country reallocation of land to crops or other uses more consistent with the yield under the new climate. However, the role of market-mediated adaptation to climate change is still poorly understood~~; except~~. Except for CDS' model, most of the applied models used in this literature present very little land heterogeneity and so cannot account for the bulk of within-country adaptation (e.g., Rosenzweig and Parry, 1994; Tsigas et al., 1997; Baldos et al., 2019). Our work provides two key insights about market-mediated adaptation.

First, market mechanisms can reverse the direction of the welfare effects indicated by the first-order productivity effects. Even if most countries lose from reduced crop productivity, some are more than compensated by terms-of-trade gains. Because total food demand is inelastic, an average decrease in crop productivity will increase food prices substantially. So, some net-food-exporting regions such as Latin America and Oceania may benefit, and the burden of adjustment to climate change may fall to net-food-importing regions, namely Asia, Europe, and the Middle East and North Africa (on such effects, see also Baldos et al., 2019).

Second, crop choice and trade adjustment have important roles in climate change adaptation. To assess the welfare effects of market adaptation, we simulate the climate change shock while alternatively holding acreage shares and bilateral import shares constant to their baseline values. These adaptation mechanisms play a large role, reducing global losses by 37% and 23%, respectively. So, change in crop choice appears to be the most important source of adaptation, but trade adjustments also play a key role. Two-third of the contribution of changes in crop choice is explained by the possibility of planting crops that could not grow under the current climate on existing fields, the rest being contributed by adjusting areas of crops that could be grown under the current climate.

The question of the role of market-mediated adaptation to climate change was recently addressed in CDS. CDS make several key methodological contributions, including the development of a new modeling approach of land allocation and the demonstration of how to harness the rich spatial data produced by crop scientists for estimations and simulations. Using counterfactual simulations, they show that restricting the fields planted with a crop under climate change conditions to be the same as the current fields would severely aggravate the impacts of climate change on welfare, tripling losses, while forcing the exported share of crops under climate change conditions to be the same as the current share would affect welfare only marginally. Some of their conclusions appear at odds with this paper's results, in particular on the role of trade. In the sensitivity analysis section, we explain these differences. On the role of trade, one can note that trade flows adjust on different margins, so there are different ways to measure the contribution of trade to adaptation. CDS show that adjustments to the exported share of crops play a limited role, a result we confirm to hold under different calibrations. On the other hand, since climate change has heterogeneous effects across countries, it can be expected that one of the main adjustment pathways of trade will be through reallocation between import sources. When we shut down this adjustment margin, it greatly increases welfare losses, thus showing that this trade margin plays a strong adaptive role.

This paper can also be linked to the recent literature evaluating gains from trade using a large class of models delivering structural gravity equations (Costinot and Rodríguez-Clare, 2014). In this literature, Fally and Sayre (2018) and Farrokhi (2020) show that accounting for the specificities of commodities leads to higher measured gains from trade. Commodities—in our case, livestock and crops—tend to be produced using sector-specific, non-tradable resources—in our case, land. These commodities have low supply elasticities because of their use of specific assets and low demand elasticities because of their essential role in downstream sectors. These features explain why commodities could contribute comparatively more to gains from trade than other sectors. We rely on similar arguments to show the importance of the role of international trade in adaptation to climate change. This recent quantitative trade literature uses exact hat algebra (Dekle et al., 2007) to identify the minimum set of information necessary for obtaining counterfactual results. However, this approach, where variables are expressed in deviation from their benchmark value, cannot be applied in models with regime change where some benchmark values are null. This is the case here. A crop potential yield may turn positive on a field because of climate change although null under current climate, and vice-versa. We show in this paper how to combine the exact hat algebra for most of the equations with a calibration in level for the equations with regime change.[1] Finally, we show how to use this method to calibrate a spatially-explicit model on a limited set of spatial information, using the country-level aggregate information and the potential productivity of land to infer where crops are planted in the initial equilibrium.

The rest of this paper is organized as follows. Section 2 develops the general equilibrium model and makes clear, using exact hat algebra, what information is needed for its calibration. Section 3 then describes the data used for calibration, distinguishing between the behavioral parameters that are selected from an extensive literature review and the baseline equilibrium values, which are constructed from various sources. The calibrated model is used in section 4 to simulate the counterfactual effects of climate change under the main calibration assumptions. In section 5, different calibrations are considered, varying the flexibility of each adjustment margin, which allows us to analyze its influence on the role of market-mediated adaptation to climate change. Section 6 offers some concluding remarks.

## 2 Model

In this section, we develop a static general equilibrium model for analysis of global agricultural trade and land use. The model modifies and extends CDS' model by representing explicitly the elasticity of final demand for agricultural products, by considering almost all agricultural land uses without possibility of extension over other land uses, and by representing livestock with the associated feed consumption, in particular pastures that account for a large part of land uses.

### 2.1 Model setup

Consider a world economy composed of multiple regions indexed by $i$ or $j \in \mathcal{I}$. Goods are indexed by $k \in \mathcal{K}$, where the non-agricultural bundle is indexed by $k = 0$. Agricultural goods include crops gathered in the set $\mathcal{K}^c \subset \mathcal{K}$ and one sector of livestock products indexed by $k = 1$. Crops are defined here extensively as anything that requires land to grow. The production of livestock requires land only indirectly through its demand of crops for feed. One crop, which we call

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[1] This mixed calibration approach was also recently used in Bergquist et al. (2019).

grass and index by $k = \mathrm{g}$, is assumed to be not tradable, because it represents forage crops that are directly grazed by animals and fodder crops (e.g., alfalfa hay) that have too low of a value-to-weight ratio to be tradable.[2] Grass is only used to feed livestock. Agricultural goods that are internationally traded, livestock and crops excluding grass, and object of final consumption are gathered in the set $\mathcal{K}^a \subset \mathcal{K}$. Each region is endowed with two factors of production, labor and land, land being only used to grow crops. Land in region $i$ comprises $F_i$ heterogeneous fields indexed by $f \in \mathcal{F}_i$ of surface $s_i^f$, each being composed of a continuum of parcels indexed by $\omega \in [0, 1]$. The outside good is produced using labor only, is freely traded, and plays the role of a numeraire.

**Preferences** The representative household in country $j$ has quasi-linear preferences over the consumption of the non-agricultural good, denoted $C_j^0$, and of the bundle of agricultural goods, $C_j$:

$$U_j = C_j^0 + \beta_j^{1/\epsilon} \begin{cases} C_j^{1-1/\epsilon}/(1-1/\epsilon) & \text{if } \epsilon \neq 1, \\ \ln C_j & \text{if } \epsilon = 1, \end{cases} \tag{1}$$

where $\epsilon > 0$ is the negative of the price elasticity of demand for the agricultural bundle and $\beta_j > 0$ parameterizes the demand for the agricultural bundle. With these preferences, the consumption of the agricultural good is inelastic to income. This is an innocuous assumption for developed countries because the small size of the agricultural sector implies that shocks affecting it are unlikely to trigger income changes large enough to affect demand. In poor countries, however, the combination of an important contribution of agriculture to GDP and of a likely higher income elasticity of food per Engel's law means that the assumption of quasi-linear preferences underestimates the reduction in food consumption caused by climate change.

The bundle of agricultural goods is a CES composite:

$$C_j = \left[ \sum_{k \in \mathcal{K}^a} \left(\beta_j^k\right)^{1/\kappa} \left(C_j^k\right)^{(\kappa-1)/\kappa} \right]^{\kappa/(\kappa-1)}, \tag{2}$$

where $\kappa > 0$ is the elasticity of substitution between agricultural products, $C_j^k$ is the final consumption of product $k$, and $\beta_j^k \geq 0$ is an exogenous preference parameter.

Following the Armington assumption, the final consumption of each agricultural good, but not the non-agricultural good, is itself a CES function of the consumption of varieties from different origins:

$$C_j^k = \left[ \sum_{i \in \mathcal{I}} \left(\beta_{ij}^k\right)^{1/\sigma} \left(C_{ij}^k\right)^{(\sigma-1)/\sigma} \right]^{\sigma/(\sigma-1)} \quad \text{for all } k \in \mathcal{K}^a, \tag{3}$$

where $\sigma > 0$ is the elasticity of substitution between varieties from different regions, $C_{ij}^k$ is the export for final consumption from region $i$ to region $j$ of good $k$, and $\beta_{ij}^k \geq 0$ is an exogenous preference parameter.

### Technology

**Non-agricultural good** The non-agricultural good is produced with labor only and constant return to scale:

$$Q_i^0 = A_i^0 N_i^0, \tag{4}$$

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[2] International trade of hay is growing but remains sufficiently low that we can neglect it here.

where $Q_i^0$ is the quantity produced, $N_i^0$ is the corresponding labor demand, and $A_i^0 > 0$ is labor productivity.

**Crops** Crops are produced by combining land and labor. Land and labor are complementary, so, on every parcel $\omega$, if the crop $k \in \mathcal{K}^c$ is planted, the production per unit of land is given by

$$Q_i^{fk}(\omega) = \min\left(A_i^{fk}(\omega), N_i^{fk}(\omega)/\nu_i^k\right), \tag{5}$$

where $A_i^{fk}(\omega) \geq 0$ is the productivity of land (the yield), $N_i^{fk}(\omega)$ is the quantity of labor used in production, and $\nu_i^k$ is the unit labor requirement per unit of land. Following CDS, we assume that yields are i.i.d. from a Fréchet distribution with shape $\theta > 1$ and scale $\gamma A_i^{fk} > 0$, where $\gamma \equiv (\Gamma(1-1/\theta))^{-1}$ is a scaling parameter such that $A_i^{fk}$ is the unconditional average yield of the field, $A_i^{fk} = \mathrm{E}[A_i^{fk}(\omega)]$, and $\Gamma(\cdot)$ is the Gamma function.[3] $\theta$ characterizes the heterogeneity within fields, with a higher $\theta$ indicating more homogeneity.

We assume that the production of grass does not require any labor. This assumption makes grass the default choice when the productivity of the other crops is not high enough and the corresponding labor costs are too high for growing them. This is consistent with the fact that pastures are more likely to be located on lands that are not the most suitable for crop production because of short growing seasons, limited water access or steep slope. However, this assumption neglects the fact that pastures and hay fields are actively managed and are not simply rangelands. This problem goes beyond this model. Agricultural statistics usually have a hard time distinguishing rangelands, pastures, and hay fields, as they concern similar plants along a continuum of management practices, so little information would be available to make the distinction in the model.

There is no need for representing other land uses in the model because the surface of each field $s_i^f$ is restricted to its surface initially used for growing crops or for pastures. This choice, which is also adopted in most of the econometric literature analyzing the impact of climate change on agriculture (Mendelsohn et al., 1994; Schlenker et al., 2005), implies that we neglect any extensive margin of land use. In the model, one cannot extend, or reduce, agricultural land use over forests, protected areas, or urban areas. Indeed, such choices are inherently dynamic—for example, foregoing annual benefits from crop production to receive future benefits from timber exploitation—they involve switching costs, and they strongly depend on local institutions and legal enforcement of legal and illegal deforestation activities. These decisions would be challenging to model and to estimate at a global scale (Scott, 2014) and so are neglected here. This choice could create a possible bias by not representing one margin of adaptation to climate change. This assumption is susceptible to underestimate the role of both production and trade adjustments because of the likely concentration of this extensive margin in the few countries with a forest frontier (e.g., Brazil and Indonesia) or with additional arable land due to climate change (e.g., Canada and Russia).

Since here the only choice of a landowner is which crop to grow on a parcel, this model neglects the possibility of changes in land management, for example by investing in irrigation, adopting new seeds, switching to double cropping, or increasing the use of fertilizers. With very heterogeneous estimation results, the size of the elasticity of yield to producer price is a contentious issue in agricultural economics that was at the heart of the recent debate on the indirect land use change effects of biofuels policies (Keeney and Hertel, 2009). In addition to their variability, available estimates concern only a small subset of the planted crops. So, we adopt the pessimistic side of the literature by assuming no yield intensification. However, we assess the sensitivity of the results to this crucial assumption.

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[3] The cumulative distribution function of a Fréchet distribution with shape parameter $\theta$ and scale parameter $s$ is given by $\Pr(X \leq x) = \exp\left(-(x/s)^{-\theta}\right)$ if $x > 0$.

**Livestock** Livestock products are produced by combining feed and labor:

$$Q_i^1 = \min\left(\frac{x_i}{\mu_i}, \frac{N_i^1}{\nu_i^1}\right), \tag{6}$$

where $x_i$ is the demand for feed and the parameter $\mu_i$ is known in zootechnics as the feed conversion ratio: the quantity of feed necessary to produce one unit of animal output.

The animal feed is produced competitively from a combination of the various crops that can be used to feed animals. The animal feed itself is not internationally traded, but its production can be made from imported crops. The composition of the feed mix depends on the country-specific composition of the livestock bundle, the animals' physiological requirements (for example the protein/fat/carbohydrate content), the local environment (temperature, humidity, public policies on manure), and the local rearing practices. Accounting for these constraints, producers of feed mix minimize their production costs that are a function of crop prices and quantities. To represent these unobservable elements, we assume that the feed mix technology takes a CES form:

$$x_i = \left[\sum_{k\in\mathcal{K}^c} \left(\beta_i^{k,\text{feed}}\right)^{1/\varsigma} \left(x_i^k\right)^{(\varsigma-1)/\varsigma}\right]^{\varsigma/(\varsigma-1)}, \tag{7}$$

where $\varsigma > 0$ is the elasticity of substitution between the various feed crops and $\beta_i^{k,\text{feed}} \geq 0$ is an exogenous technological parameter. For the sake of parsimony, the bundles of imported and domestic crops used to produce the animal feed, $x_i^k$, are obtained using the same Armington aggregator used for composite final goods, given by equation (3).

**Market structure and trade costs** All markets, including the labor market, are perfectly competitive. Labor is perfectly mobile between sectors. Despite the land heterogeneity between fields, we neglect domestic trade costs and assume that all producers in a region receive the same price for a crop. This is also the case for grass, which is only assumed to be non-tradable internationally. This assumption greatly simplifies the modeling of livestock by avoiding the need to represent livestock production by field.

Except for the outside good, international trade entails trade costs. We consider iceberg trade costs. $\tau_{ij}^k \geq 1$ units must be shipped from country $i$ to country $j$ to sell a variety of sector $k$. The absence of arbitrage opportunities implies that

$$p_{ij}^k = \tau_{ij}^k p_i^k \text{ for all } k \in \mathcal{K}^a, \tag{8}$$

where $p_i^k$ is the producer price of gook $k$ in region $i$ and $p_{ij}^k$ is its import price in region $j$.

## 2.2 Equilibrium in levels

**Good demand** Given the households quasi-linear preferences in equation (1), utility maximization implies the following demand for the bundle of agricultural products:

$$C_j = \begin{cases} \beta_j P_j^{-\epsilon} & \text{if } E_j \geq \beta_j P_j^{1-\epsilon}, \\ E_j/P_j & \text{if } E_j < \beta_j P_j^{1-\epsilon}, \end{cases} \tag{9}$$

where $E_j$ is the country expenditures and $P_j$ is the price of the bundle of agricultural goods given by

$$P_j = \left[ \sum_{k \in \mathcal{K}^a} \beta_j^k \left( P_j^k \right)^{1-\kappa} \right]^{1/(1-\kappa)}, \tag{10}$$

where $P_j^k$ is the composite price of imports of good $k$.

From equation (2), the demand of the bundle of product $k \in \mathcal{K}^a$ is given by

$$C_j^k = \beta_j^k \left( \frac{P_j^k}{P_j} \right)^{-\kappa} C_j. \tag{11}$$

The demand for the outside good is given by the household's budget constraint:

$$C_j^0 = E_j - P_j C_j. \tag{12}$$

It can possibly be equal to 0 if $E_j < \beta_j P_j^{1-\epsilon}$.

**Production** Zero profit, absence of trade barriers, and the numeraire assumption in the non-agricultural sector imply the equality of the labor productivity parameter to wage, $w_i$:

$$A_i^0 = w_i, \tag{13}$$

which will be used below to substitute $w_i$ away.

From equations (6) and (7), cost minimization in the livestock feed sector implies for $k \in \mathcal{K}^c$:

$$p_i^{\mathrm{l}} = \nu_i^{\mathrm{l}} A_i^0 + \mu_i P_i^{\mathrm{feed}}, \tag{14}$$

$$x_i^k = \beta_i^{k,\mathrm{feed}} \left( \frac{P_i^k}{P_i^{\mathrm{feed}}} \right)^{-\varsigma} \mu_i Q_i^{\mathrm{l}}, \tag{15}$$

$$P_i^{\mathrm{feed}} = \left[ \sum_{k \in \mathcal{K}^c} \beta_i^{k,\mathrm{feed}} \left( P_i^k \right)^{1-\varsigma} \right]^{1/(1-\varsigma)}, \tag{16}$$

where $P_i^{\mathrm{feed}}$ is the price index corresponding to the demand for the feed bundle $x_i = \mu_i Q_i^l$.

The Leontief structure of crop production in equation (5) implies for parcel $\omega$ the following factor demands per unit of land if the parcel is planted with $k \in \mathcal{K}^c$:

$$Q_i^{fk}(\omega) = A_i^{fk}(\omega) = N_i^{fk}(\omega) / \nu_i^k. \tag{17}$$

The difference between the revenue from crop production and the labor cost is the land rent. The rent accruing to the parcel of land $\omega$ when used to grow $k$ is

$$p_i^k Q_i^{fk}(\omega) - A_i^0 N_i^{fk}(\omega) = \left( p_i^k - A_i^0 \nu_i^k \right) A_i^{fk}(\omega), \tag{18}$$

which is distributed according to a Fréchet with parameters $\theta$ and $\gamma r_i^k A_i^{fk}$ if $r_i^k > 0$ and where

$$r_i^k \equiv p_i^k - A_i^0 \nu_i^k \tag{19}$$

is the land rent per unit of production at the country level.

To maximize its profit, the landowner plants a parcel with the crop delivering the highest land rents, $r_i^k A_i^{fk}(\omega)$. Given that the land rents follow a Type-II extreme value distribution, the acreage choice is a discrete choice problem and the probability that crop $k$ is the most profitable crop is given by

$$\pi_i^{fk} = \frac{\left(r_i^k A_i^{fk}\right)^\theta}{\sum_{l \in \mathcal{K}^c, r_i^l \geq 0} \left(r_i^l A_i^{fl}\right)^\theta}. \tag{20}$$

Since on each field there is a continuum of parcels with the same probability of acreage choice, $\pi_i^{fk}$ is also the share of field $f$ in country $i$ planted with crop $k$.

Total output of crop $k$ by field $f$ is given by the product of the surface of the field, the share of acreage devoted to crop $k$, and the average yields conditional on the crop having been chosen for production:

$$Q_i^{fk} = s_i^f \pi_i^{fk} \mathrm{E}\left[A_i^{fk}(\omega) \,|r_i^k A_i^{fk}(\omega) \in \operatorname*{arg\,max}_{l \in \mathcal{K}^c} r_i^l A_i^{fl}(\omega)\right]. \tag{21}$$

From the standard properties of the Fréchet distribution, we have

$$E\left[r_i^k A_i^{fk}(\omega) \,|r_i^k A_i^{fk}(\omega) \in \operatorname*{arg\,max}_{l \in \mathcal{K}^c} r_i^l A_i^{fl}(\omega)\right] = \left[\sum_{l \in \mathcal{K}^c, r_i^l \geq 0} \left(r_i^l A_i^{fl}\right)^\theta\right]^{1/\theta}, \tag{22}$$

so

$$Q_i^{fk} = s_i^f A_i^{fk} \left(\pi_i^{fk}\right)^{(\theta-1)/\theta}, \tag{23}$$

and country-level production is

$$Q_i^k = \sum_{f \in \mathcal{F}_i} s_i^f A_i^{fk} \left(\pi_i^{fk}\right)^{(\theta-1)/\theta}. \tag{24}$$

Similarly, the total land rents from growing crop $k$ are

$$R_i^k = \sum_{f \in \mathcal{F}_i} s_i^f \pi_i^{fk} E\left[r_i^k A_i^{fk}(\omega) \,|r_i^k A_i^{fk}(\omega) \in \operatorname*{arg\,max}_{l \in \mathcal{K}^c} r_i^l A_i^{fl}(\omega)\right] = r_i^k Q_i^k. \tag{25}$$

Based on the previous equations, one can calculate the own-price supply elasticity for crops which is given by

$$\frac{\partial \ln Q_i^k}{\partial \ln p_i^k} = (\theta - 1) \frac{p_i^k}{r_i^k} \sum_{f \in \mathcal{F}_i} \left(1 - \pi_i^{fk}\right) \frac{Q_i^{fk}}{Q_i^k}. \tag{26}$$

$\theta$ appears as the parameter governing supply elasticity. A higher $\theta$, which corresponds to more homogeneous fields, also implies a more elastic supply. The second term, the ratio of producer price to land rent $p_i^k / r_i^k$, allows conversion of the supply elasticity with respect to land rents into the own-price elasticity. It is greater than 1, as it equals 1 plus the ratio of unit labor costs to land rents. The last term, $\sum_{f\in\mathcal{F}_i}(1-\pi_i^{fk})Q_i^{fk}/Q_i^k$, shows that the elasticity is non-constant and depends on the acreages. For a crop with very small acreages, $\pi_i^{fk}\approx 0$, the elasticity is $(\theta-1)\,p_i^k/r_i^k$. The elasticity decreases when acreages increase, eventually reaching 0 when $\pi_i^{fk}\approx 1$.

**International trade** Preferences over the countries of origin have been assumed similar for final consumption and for livestock feed, so based on equation (3), the index price that aggregates the price of varieties from various origins is

$$P_j^k = \left[\sum_{i\in\mathcal{I}}\beta_{ij}^k\left(\tau_{ij}^k p_i^k\right)^{1-\sigma}\right]^{1/(1-\sigma)} \quad \text{for all } k\in\mathcal{K}^a, \tag{27}$$

and total import demand is equal to the sum of demand for final consumption and for livestock feed, if relevant:

$$X_j^k/P_j^k = C_j^k + \mathbf{1}_{k\in\mathcal{K}^c}\left(x_j^k\right) \text{ for all } k\in\mathcal{K}^a, \tag{28}$$

where $X_j^k$ is the value of imports and $\mathbf{1}_{(\cdot)}$ is the indicator function. Lastly, the value of exports of good $k\in\mathcal{K}^a$ from country $i$ to country $j$ is given by

$$X_{ij}^k = \beta_{ij}^k\left(\frac{\tau_{ij}^k p_i^k}{P_j^k}\right)^{1-\sigma} X_j^k. \tag{29}$$

**Market clearing conditions** The market equilibrium for goods is given by the equality between the value of production and export demand from all countries:

$$p_i^k Q_i^k = \sum_{j\in\mathcal{I}} X_{ij}^k. \tag{30}$$

**Budget constraint** Final expenditure in country $i$ is the sum of labor income, land rents, and trade deficits denoted $\Delta_i$:

$$E_i = A_i^0 N_i + \sum_{k\in\mathcal{K}^c} r_i^k Q_i^k + \Delta_i. \tag{31}$$

From the above we can define the competitive equilibrium as follows

**Definition.** A competitive equilibrium is a vector of consumption of the bundle of agricultural goods ($C_i$), price of the bundle of agricultural goods ($P_i$), final consumption of goods ($C_i^k$), production ($Q_i^k$), feed demand ($x_i^k$), aggregate feed price ($P_i^{\text{feed}}$), land rent per unit of production ($r_i^k$), acreage share ($\pi_i^{fk}$), consumption price ($P_i^k$), total imports ($X_i^k$), bilateral exports ($X_{ij}^k$), producer price ($p_i^k$), and expenditures ($E_i$) such that equations (9)–(12), (14)–(16), (19), (20), (24), and (27)–(31) hold.

## 2.3 Equilibrium in relative changes

To make the data necessary to calibrate this model explicit, when possible we express the model in relative changes, with $\hat{v}\equiv v'/v$ the relative changes of any variable $v$ between the baseline and the counterfactual equilibria where it takes the value $v'$. We consider one source of exogenous shocks: changes in crop productivity.

To express the equations in relative changes, we introduce share parameters. $\alpha_j^k = P_j^k C_j^k/P_j C_j$ is the budget share of product $k$ in the consumption of all agricultural goods. $\alpha_j^{k,\text{feed}} = P_j^k x_j^k/P_j^{\text{feed}} x_j$ is the budget share of crop $k$ in livestock feed. $\alpha_{ij}^k = X_{ij}^k/X_j^k$ is the bilateral trade share. Finally, we introduce $\phi_i^{k,\text{labor}}$, $\phi_i^{k,\text{land}}$, and $\phi_i^{k,\text{feed}}$ the budget shares of each input of production: labor, land, and feed. They allow us to express the zero-profit condition in the same way for all sectors as

$$\hat{p}_i^k = \phi_i^{k,\text{labor}} + \phi_i^{k,\text{land}} \hat{r}_i^k + \phi_i^{k,\text{feed}} \hat{P}_i^{\text{feed}}. \tag{32}$$

To allow for the possibility that fields may have zero potential yields in some crops in the baseline but positive yields under climate change, crop production is expressed using a mix of variables in levels and variables in relative changes. In particular, production depends on $A_i^{fk\prime}$, the counterfactual levels of crop productivity, since $\hat{A}_i^{fk}$ would not be defined with zero initial potential yield. Consequently, after substitution of the acreage share, the equation associated with crop production is

$$\hat{Q}_i^k = \sum_{f \in \mathcal{F}_i} \frac{s_i^f A_i^{fk\prime}}{Q_i^k} \frac{\left(r_i^k \hat{r}_i^k A_i^{fk\prime}\right)^{\theta-1}}{\left[\sum_{l \in \mathcal{K}^c} \left(r_i^l \hat{r}_i^l A_i^{fl\prime}\right)^{\theta}\right]^{(\theta-1)/\theta}} \text{ for all } k \in \mathcal{K}^c. \tag{33}$$

This equation mixes variables in relative changes with their initial baseline values, $r_i^k$ and $Q_i^k$, that are unobservable. We explain below how they can be recovered from other observables using the landowner optimality conditions.[4]

After removing the trade deficits,[5] all the other equations follow simply from their expression in levels, and if not otherwise precised, the following equations hold for all $i, j \in \mathcal{I}$, $k \in \mathcal{K}$, and $k \neq 0$:

$$\hat{P}_j = \left[\sum_{k \in \mathcal{K}^a} \alpha_j^k \left(\hat{P}_j^k\right)^{1-\kappa}\right]^{1/(1-\kappa)}, \tag{34}$$

$$\hat{C}_j^k = \left(\hat{P}_j^k\right)^{-\kappa} \left(\hat{P}_j\right)^{\kappa-\epsilon} \text{ for all } k \in \mathcal{K}^a, \tag{35}$$

$$P_j^0 C_j^0 \hat{C}_j^0 = E_j \hat{E}_j - P_j C_j \left(\hat{P}_j\right)^{1-\epsilon}, \tag{36}$$

$$\hat{x}_j^k = \left(\hat{P}_j^k / \hat{P}_j^{\text{feed}}\right)^{-\varsigma} \hat{Q}_j^1 \text{ for all } k \in \mathcal{K}^c, \tag{37}$$

$$\hat{P}_j^{\text{feed}} = \left[\sum_{k \in \mathcal{K}^c} \alpha_j^{k,\text{feed}} \left(\hat{P}_j^k\right)^{1-\varsigma}\right]^{1(1-\varsigma)}, \tag{38}$$

$$\hat{P}_j^k = \left[\sum_{i \in \mathcal{I}} \alpha_{ij}^k \left(\hat{p}_i^k\right)^{1-\sigma}\right]^{1/(1-\sigma)}, \tag{39}$$

$$X_j^k \hat{X}_j^k = P_j^k C_j^k \hat{P}_j^k \hat{C}_j^k + \mathbf{1}_{k \in \mathcal{K}^c} \left(P_j^k x_j^k \hat{P}_j^k \hat{x}_j^k\right), \tag{40}$$

$$\hat{X}_{ij}^k = \left(\hat{p}_i^k / \hat{P}_j^k\right)^{1-\sigma} \hat{X}_j^k, \tag{41}$$

$$p_i^k Q_i^k \hat{p}_i^k \hat{Q}_i^k = \sum_{j \in \mathcal{I}} X_{ij}^k \hat{X}_{ij}^k, \tag{42}$$

$$E_i \hat{E}_i = A_i^0 N_i + \sum_{k \in \mathcal{K}^c} R_i^k \hat{r}_i^k \hat{Q}_i^k. \tag{43}$$

These equations make clear the information needed for calibrating the model, and the mapping with the data is

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[4] Another source of regime change could prevent expressing the model in relative changes: the fact that with a quasi-linear utility the consumption of the outside good can reach zero if income is not high enough compared to relative prices. This is an exceptional situation, possible only for extreme calibration/shocks, so we neglect its possibility and verify after the simulations that we are still in the interior solution.

[5] To impose a long-run situation in the initial equilibrium consistent with a shock at the 2080s horizon, we remove trade deficits. In this model, this amounts to reducing initial expenditures, $E_i$, and consumption of the outside good, $P_i^0 C_i^0$, by the negative of the trade deficits, $-\Delta_i$.

discussed in section 3. Only one aspect deserves further discussion here: the calibration of the land rent per unit of production, $r_i^k$, and the volume of crop production, $Q_i^k$, in equation (33). We show now that given field-level potential yields, $A_i^{fk}$, and aggregate moments, we can uniquely recover these initial values. Using equations (20), (24), and (25), we have

$$\left(r_i^k\right)^{-\theta} = \left(R_i^k\right)^{-1} \sum_{f\in\mathcal{F}_i} s_i^f \left(A_i^{fk}\right)^{\theta} \left[\sum_{l\in\mathcal{K}^c} \left(r_i^l A_i^{fl}\right)^{\theta}\right]^{(1-\theta)/\theta}. \tag{44}$$

Using the contraction mapping theorem, we show in Appendix **??** that this equation has a unique solution. So, for each country, given positive values for $R_i^k$, $s_i^f$ , and $A_i^{fk}$, from any set of initial positive land rents, $\left\{r_i^k > 0 | k \in \mathcal{K}^c, R_i^k > 0\right\}$, one can do a fixed-point iteration between the right-hand side and the left-hand side, which will converge to the equilibrium value of land rents. From the equilibrium values of $r_i^k$, we can calculate the acreage shares, $\pi_i^{fk}$, from equation (20) and the initial production levels, $Q_i^k$, from equation (24).[6]

The model results would be similar if a country-crop productivity shifter was used to adjust the potential yields $A_i^{fk}$ (see proof in Appendix **??**).[7] This is an important result because the potential yields we rely on for calibration can be very different from the realized yields. They can differ, for example, because of yield gaps, multiple cropping, or technological changes with respect to the time period of the data underlying the crop model calibration. The invariance to the presence of productivity shifters implies that the model presents some robustness to measurement errors in the potential yields as long as they exist along the country-crop dimension and stay constant across the climate scenarios. It also means that the model does not need to account for the economic and institutional reasons that may explain the low levels of yields in low-income countries. Consequently, what matters for calibrating field-level information is the difference between fields for a given country-crop couple.

Equations (32)–(43) represent a square system of nonlinear equations and can be solved with any solver for systems of nonlinear equations. In this paper, the model is solved using the solvers available under GAMS.[8]

## 2.4 Welfare

Welfare changes from climate change are evaluated by calculating the equivalent variation.[9] The household expenditure function is

$$e\left(P_j^0, P_j, U_j\right) = P_j^0 U_j + \beta_j \left(P_j^0\right)^{\epsilon} \begin{cases} P_j^{1-\epsilon}/(1-\epsilon) & \text{if } \epsilon \neq 1, \\ \left[1 - \ln\left(\beta_j P_j^0 / P_j\right)\right] & \text{if } \epsilon = 1. \end{cases} \tag{45}$$

The equivalent variation expressed in terms of variables in relative changes is

$$EV_j = e\left(P_j^0, P_j, U_j'\right) - e\left(P_j^0, P_j, U_j\right) = P_j^0 C_j^0 \left(\hat{C}_j^0 - 1\right) + P_j C_j \begin{cases} \left(\hat{C}_j^{1-1/\epsilon} - 1\right)/(1 - 1/\epsilon) & \text{if } \epsilon \neq 1, \\ \ln \hat{C}_j & \text{if } \epsilon = 1. \end{cases} \tag{46}$$

To help interpret the welfare results, we approximate the equivalent variation at the first order (see Appendix **??**).

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[6] This strategy is similar in spirit to Costinot and Donaldson's (2016) calibration strategy that relies on the combination of optimality conditions and observation of aggregate statistics ($R_i^k$ in our case) and detailed productivity information ($A_i^{fk}$ in our case) to recover the detailed allocation.

[7] This property results from the assumption that the labor requirement is the same within a country for a given crop in equation (5). This allows us to define a unique index of land rents at the country level, $r_i^k$, that can absorb the shifter in calibration. This implies that the model calibration only requires information about the initial values in dollars and about the relative productivity between fields. The additional information about the yields in ton/ha is redundant, since the model has no use for tons. So, we have one degree of freedom corresponding to the potential country-crop productivity shifter.

[8] Data and programs to replicate the paper's results are available at DOI: 10.15454/HYUURI.

[9] In this setting of a *de facto* partial equilibrium model where the price of the outside good is constant and the representative household has quasi-linear utility, the equivalent variation is equal to the consumer surplus and the compensating variation.

Neglecting changes in trade deficits that will be removed before simulating the effects of climate change, it gives the following decomposition:

$$\mathrm{d}\,EV_j = \underbrace{\sum_{k\in\mathcal{K}^a, i\in\mathcal{I}} \left(X_{ji}^k \,\mathrm{d}\ln p_j^k - X_{ij}^k \,\mathrm{d}\ln p_i^k\right)}_{\text{Terms-of-trade effects}} + \underbrace{\sum_{f\in\mathcal{F}_j, k\in\mathcal{K}^c} r_j^k Q_j^{fk} \,\mathrm{d}\ln A_j^{fk}}_{\text{Productivity effects}}. \tag{47}$$

In the absence of any distortion in the model, this decomposition is very simple with two terms. The first is the welfare effect of changes in terms of trade. They sum to zero at the world level. The second is the welfare effect of changes in crop yields at the initial acreage choices and prices.

This decomposition approximates the welfare changes for small changes. The changes in yield from climate change are large, on average −13.2%, and values such as −50% or +50% are not unusual, so these are not marginal changes that would make the first-order approximation in equation (47) valid. With these large changes, the first-order approximation is very imprecise. To obtain a precise decomposition of the welfare changes, we follow Harrison et al.'s (2000) method and integrate the welfare decomposition along a line:

$$EV_j = \sum_{k\in\mathcal{K}^a, i\in\mathcal{I}} \int_{t=0}^{1} \left(X_{ji}^k(t) \frac{\mathrm{d}\ln p_j^k}{\mathrm{d}t} - X_{ij}^k(t) \frac{\mathrm{d}\ln p_i^k}{\mathrm{d}t}\right) \mathrm{d}t + \sum_{f\in\mathcal{F}_j, k\in\mathcal{K}^c} \int_{t=0}^{1} r_j^k(t)\, Q_j^{fk}(t) \frac{\mathrm{d}\ln A_j^{fk}}{\mathrm{d}t} \mathrm{d}t, \tag{48}$$

where $t$ parameterizes the yield changes. The resulting decomposition is known to be path-dependent, as terms-of-trade and productivity effects could react differently depending on which countries or crops are affected first. Without any information on the timing of yield changes, we simply divide yields regularly between their initial and final values: $tA_j^{fk\prime} + (1-t)\,A_j^{fk}$. We will complement the interpretation of this decomposition with other results going in the same directions, mitigating concerns about the path-dependency.

## 3 Taking the model to the data

When calibrating the model, it is important to represent most agricultural commodities for two reasons. First, it allows all the behavioral parameters to be clearly mapped to elasticities commonly estimated in the literature. For example, if almost all agricultural products are included in the model, then the top elasticity $\epsilon$ can be interpreted as the negative of the price elasticity of demand for agricultural products, for which there are estimates in the structural transformation literature (Comin et al., forthcoming). With a small subset of agricultural commodities, this elasticity would be more difficult to interpret, as it would be a composite of the price elasticity of demand for agricultural products and of the elasticity of substitution between crops in the model and the non-represented crops. Second, some crops may make a minor contribution to global crop production but be of crucial importance in some countries. For example, roots and tubers such as cassava, sweet potatoes, or yams are staple foods in many African countries even if they represent a small share of global crop production and an even smaller share of trade. Lastly, climate change will affect all crops differentially. So, neglecting some crops with non-negligible land use would imply not taking into account the opportunity cost of reallocating production on the land they were previously grown.

The model is calibrated on 35 crops and 50 countries/regions with a 2011 base year for the data. Table 2 lists the countries and crops included in the sample and indicates their respective share of world agricultural area and world output in value. For computational reasons, all countries are not included separately, but countries that are not are aggregated in 9 regions based on their geographical location (mapping between regions and countries available in table **??**). The countries represented separately have been chosen based on their share of world output in crops and their share of world agricultural area, but also chosen to illustrate a diversity of exposures to climate change. All crops from the GAEZ project with a mapping with FAOSTAT crops have been included in the model, but some have been aggregated. Excluding grass, the crops represented in the model correspond to 88% of the 2011 global harvested areas in FAOSTAT and therefore to an even higher share of agricultural land uses when pastures are accounted for.

Table 2: List of sample countries and crops

| Country | Share of world ag. area (%)[a] | Share of world output (%)[b] | Country | Share of world ag. area (%)[a] | Share of world output (%)[b] |
|---|---|---|---|---|---|
| Argentina | 3.27 | 1.21 | Pakistan | 0.74 | 1.37 |
| Australia | 6.87 | 1.34 | Peru | 0.53 | 0.41 |
| Bangladesh | 0.22 | 0.47 | Philippines | 0.24 | 0.83 |
| Brazil | 5.70 | 5.10 | Poland | 0.40 | 0.79 |
| Canada | 1.10 | 1.47 | Romania | 0.32 | 0.50 |
| China (including Hong Kong) | 9.97 | 21.20 | Russia | 3.90 | 2.41 |
| Colombia | 0.88 | 0.65 | Senegal | 0.20 | 0.05 |
| Egypt | 0.10 | 0.60 | South Africa | 2.11 | 0.55 |
| Ethiopia | 0.88 | 0.37 | Spain | 0.59 | 1.57 |
| France | 0.74 | 2.44 | Sri Lanka | 0.06 | 0.10 |
| Germany | 0.42 | 2.20 | Thailand | 0.40 | 0.88 |
| Greece | 0.10 | 0.45 | Turkey | 0.87 | 1.46 |
| India | 4.40 | 8.19 | Ukraine | 1.03 | 0.74 |
| Indonesia | 1.55 | 2.92 | United Kingdom | 0.39 | 1.14 |
| Iran | 1.32 | 0.94 | United States | 8.58 | 11.10 |
| Italy | 0.25 | 1.71 | Viet Nam | 0.23 | 0.68 |
| Japan | 0.10 | 2.53 | Caribbean | 0.31 | 0.49 |
| Kazakhstan | 5.06 | 0.47 | Central America | 0.56 | 0.61 |
| Kenya | 0.68 | 0.21 | Rest of Asia | 3.57 | 1.67 |
| Korea, South | 0.03 | 0.80 | Rest of Commonwealth of Independent States | 2.13 | 1.06 |
| Malaysia | 0.19 | 0.68 | Rest of Europe | 1.40 | 4.04 |
| Mexico | 2.37 | 1.32 | Rest of Middle East and North Africa | 2.45 | 2.21 |
| Morocco | 0.57 | 0.35 | Rest of Oceania | 0.27 | 0.60 |
| Netherlands | 0.05 | 0.82 | Rest of South America | 2.91 | 1.48 |
| Nigeria | 1.48 | 1.29 | Rest of Sub-Saharan Africa | 17.48 | 3.50 |
| Crop | | | Crop | | |
| Banana | | 1.59 | Olive | | 0.59 |
| Barley | | 0.83 | Onion | | 0.92 |
| Beans | | 0.61 | Other pulses | | 0.46 |
| Buckwheat | | 0.03 | Peas | | 0.11 |
| Cabbage | | 0.50 | Rapeseed | | 0.97 |
| Carrot | | 0.35 | Rice | | 8.83 |
| Citrus fruits | | 1.70 | Rye | | 0.08 |
| Cocoa | | 0.23 | Sorghum | | 0.43 |
| Coconut | | 0.31 | Soybean | | 3.21 |
| Coffee | | 0.58 | Sugar crops | | 3.08 |
| Cotton | | 2.51 | Sunflower | | 0.52 |
| Flax | | 0.03 | Tea | | 0.34 |
| Grass | | 47.82 | Tobacco | | 0.52 |
| Groundnut | | 0.92 | Tomato | | 2.48 |
| Maize | | 6.56 | Tropical roots and tubers | | 3.24 |
| Millet | | 0.27 | Wheat | | 5.05 |
| Oat | | 0.12 | White potato | | 2.86 |
| Oil palm | | 1.35 | | | |

Sources: [a] Based on agricultural area in Ramankutty and Foley (1999) extended to 2007. [b] Shares calculated on model values in 2011 $ for the initial equilibrium based on FAOSTAT and GTAP as described in Appendix **??**.

## 3.1 Behavioral parameters

After having properly harmonized the concept and definition of the parameters in the model with available estimates, we rely on a literature review to select the behavioral parameters. We turn to this strategy because of the difficulties faced in estimating these parameters in a framework consistent with our model. Our model being similar to CDS', we could have adopted their estimation approach. However, Appendix **??** replicates their estimations and shows that they suffer from important problems. On the demand side, estimating the elasticities $\sigma$ and $\kappa$ requires successive estimations, which requires bootstrapping to obtain appropriate standard errors. Once bootstrapped, CDS' ~~estimates are~~ estimate of $\kappa$ is no longer significant. In Appendix **??**, we propose another approach: estimating the elasticity of substitution between varieties from a standard gravity regression on tariffs. However, collinearity prevents the identification of the fixed effects, and so, any estimation of the elasticities in upper nests ($\kappa$, $\varsigma$, and $\epsilon$).

On the supply side, two problems prevent estimating $\theta$, the parameter governing the acreage elasticities. They are detailed in Appendix **??** for the case of CDS' estimation but are similar in our setting. The first problem is the absence of official statistics at the global level on physical acreages by crop that could be mapped to the model variables. The only available statistics, from FAOSTAT and used in the estimations in CDS, concern harvested areas, that is, the physical areas planted with a crop multiplied by the number of times they are harvested in the year. In tropical countries, the same fields can be planted and harvested several times a year, so physical and harvested areas can be very different, but the variables of interest in the model are the physical areas. In the case of Bangladesh in 2010, the sum of all harvested areas (which does not include pastures) is 15.2 million hectares, more than the country area and almost double the FAOSTAT figure for area under arable land and permanent crops. So, each field is harvested twice a year on average. Relying on harvested areas instead of physical areas is likely to severely bias the estimations. The second problem is related to the imprecise mapping between the available potential yields information and the locally relevant ones. Because of multiple cropping or different input levels between the crop model and the reality, there can be systematic differences between potential and realized yields, preventing credible identification (see in Appendix **??** for the consequences that unrealistically low potential yields for tomatoes have on other crops land allocation). The estimation in CDS suffers from this problematic mapping between the model and data.

Since cross-section estimations are not feasible for this model, we rely on existing estimations, mostly at the country level, of the elasticities of interest. We detail below their sources and how they map to the elasticities in the model.

**Price elasticity of agricultural good demand** Given that the model includes almost all agricultural products, the elasticity $\epsilon$ can be approximated as a demand elasticity for agricultural goods. In the form of an elasticity of substitution between agriculture, manufacturing and services, this elasticity is central in the literature on structural transformation in macroeconomics. It is commonly assumed to be less than 1 to reproduce the stylized facts of structural transformation. The recent cross-country estimates of Comin et al. (forthcoming) point toward a value of 0.5 for the world, with a higher value for OECD countries and a lower value for non-OECD countries, but always significantly below 1. We follow Comin et al.'s estimate for the world and take $\epsilon = 0.5$.

**Elasticity of substitution between agricultural products for final demand** To choose the elasticity of substitution between agricultural products for final demand, one should first note that this elasticity determines the price elasticity of final demand for agricultural goods jointly with the price elasticity of demand for the agricultural bundle and the budget shares. From equations (34)–(35), this elasticity is

$$\frac{\partial \ln C_j^k}{\partial \ln P_j^k} = -\kappa + (\kappa - \epsilon)\, \alpha_j^k. \tag{49}$$

This formula implies that the demand elasticity is bounded between $-\kappa$ for a budget share close to 0 and $-\epsilon$ for a budget share close to 1.

Food demand elasticities are a topic that has been studied extensively. A meta-analysis of U.S. price elasticities for food products (Andreyeva et al., 2010) finds mean elasticities between −0.75 and −0.27 (excluding beverages and food away from home). Similar elasticities have been found in a meta-analysis on China (Chen et al., 2016), with elasticities between −0.86 and −0.33. These meta-analyses are based on estimations using household survey data, but the elasticities estimated at the country-level using cross-country ICP data by Muhammad et al. (2011) are very close. Based on this literature, we assume $\kappa = 0.6$, which targets the typical elasticity in this literature.

**Elasticity of substitution between agricultural products for feed demand** We proceed similarly for the elasticity of substitution between agricultural products for feed demand. Let us first note that it governs the price elasticity of feed demand. From equations (37) and (38):

$$\frac{\partial \ln x_i^k}{\partial \ln P_i^k} = -\varsigma\left(1-\alpha_i^{k,\text{feed}}\right). \tag{50}$$

So, feed demand elasticities vary between $-\varsigma$ and 0.

There is a limited and often dated literature on the estimation of feed demand. The most recent work is Beckman et al. (2011). Beckman et al. estimate feed demand elasticities on data simulated from a least-cost ration model of the U.S. feed market. Their estimates vary between −1.9 and −0.05, depending on the feed products and the livestock sectors. Peeters and Surry (1993) and Rude and Meilke (2000) estimate feed input demand equations on time-series. Using Belgian data, Peeters and Surry (1993) find feed demand elasticities, aggregated over all livestock sectors, to be between −0.79 and −0.21. Using European data, Rude and Meilke (2000) find elasticities between −2.13 and −0.32. Feed demand elasticities tend to be higher than food demand elasticities, some exceeding 1 in absolute value, which is consistent with feed choice being more a matter of economic and technical choice rather than a matter of individual preferences, as food choice can be. These elasticities also vary substantially between sources and between livestock sectors. Based on this literature, we assume $\varsigma = 0.9$.

**Elasticity of substitution between varieties** For the elasticity of substitution between varieties, we propose an estimation on tariffs in Appendix **??**. Since our 2SLS estimates include in their confidence interval CDS' estimation of 5.4, we retain this value~~to limit the differences between the models. This value~~, which is also close to what the meta-analysis of Head and Mayer (2014, section 4.2) have found to be the typical trade elasticity ($1-\sigma$ in the model), −5. But, we should note that there is a large variety of estimates for the agricultural sector in the gravity literature. For example, Caliendo and Parro's (2015) preferred estimate of the trade elasticity for agricultural products is −9, almost twice as large as CDS' estimate~~, which would lead to even higher trade reallocations~~. We will consider this value in the sensitivity analysis in section 5 as well as $\sigma = 3$, a value close to our OLS estimates (table **??**) and to 2SLS estimates following CDS' method but excluding missing prices (table **??**).

**Degree of within-field heterogeneity** From equation (26), $\theta$, the degree of within-field heterogeneity, is the parameter governing the acreage elasticity. Ideally, we would like to obtain this parameter from cross-country estimates of crop-level elasticities. However, to our knowledge, such estimates do not exist (except for CDS estimates that are discussed in Appendix **??**). The closest paper to this ideal would be Haile et al. (2016) which estimates supply and acreage elasticities of maize, rice, soybean, and wheat from a country-level panel. For our purpose, the limits of their approach are twofold. First, they use international prices instead of domestic prices. Second, most of the identification does not come from the cross-sectional dimension but from the temporal dimension, since, except for different crop calendars, different countries face the same prices. Their estimated supply elasticities are 0.23, 0.06, 0.37, and 0.11 for maize, rice, soybean, and wheat, respectively (estimated acreage elasticities are lower).

There is, however, an abundant literature about the estimation of country-level acreage elasticities, at least in developed countries and for the most important crops. There is no recent survey on this question. The most recent one (Rao, 1989), thirty years ago, pointed to crop-specific long-run elasticities between 0.3 and 1.2 in developing countries. More recent evidence is available on the acreage elasticities of maize and soybean in the U.S., which have been studied extensively. Table 3 reports these elasticities from different studies. These estimates display large variability, part of which is likely related to the regular changes in farm policies and thus farmers' incentives, and part of which is related to changes in methods. A lot of early estimations were on time-series, resulting in lower estimates, while recent works are more likely to use panel data and to control for the endogeneity of prices if estimating at an aggregate level (e.g., Miao et al., 2016; Li et al., 2019). The latest four estimates fit our needs most closely, with the identification not relying entirely on the temporal dimension. The estimates are all below 1, ranging from 0.2 to 0.6.

Table 3: Estimates of acreage elasticities in the U.S. in different studies

| Study | Maize | Soybean | Type of data and estimation method |
|---|---|---|---|
| Lee and Helmberger (1985) | 0.05 | 0.25 | State-level panel, Aitken GLS |
| Tegene et al. (1988) | 0.20 | | Time series of Iowa aggregates, 3SLS |
| Shideed and White (1989) | 0.19 | 0.41 | Country-level time series, OLS |
| Chavas and Holt (1990) | 0.15 | 0.45 | Country-level time series, SUR |
| Chembezi and Womack (1992) | 0.10 | | Country-level time series, GLS |
| Orazem and Miranowski (1994) | 0.10 | 0.33 | County-level (Iowa) panel, Maximum Likelihood |
| Miller and Plantinga (1999) | 0.95 | 0.95 | Time series of 3 selected Iowa counties, Maximum Entropy |
| Arnade and Kelch (2007) | 0.01 | 0.05 | Time series of Iowa aggregates, SUR |
| Lin and Dismukes (2007) | 0.17–0.35 | 0.30 | State-level pooled time series and cross-section, SUR |
| Hendricks et al. (2014, long-run elasticities) | 0.29 | 0.26 | Field-level panel, discrete choice model |
| Miao et al. (2016) | 0.45 | 0.63 | County-level panel FE with IV |
| Kim and Moschini (2018, long-run elasticities) | 0.39 | 0.26 | County-level panel GMM |
| Li et al. (2019) | 0.21 | | County-level panel FE with IV |

Source: Adapted from Miao et al. (2016, table 1) and Kim and Moschini (2018, table 5).

Similar elasticities have been estimated in a European setting (e.g., Lacroix and Thomas, 2011; Carpentier and Letort, 2013). From this literature review, we target an average world acreage elasticity, weighted by the value of production, of 0.5. To calculate the elasticities, one needs the values of $p_i^k/r_i^k$, $\pi_i^{fk}$, and $Q_i^{fk}/Q_i^k$. $p_i^k/r_i^k$ is not observed, but $p_i^k Q_i^k / r_i^k Q_i^k = 1/\phi_i^{k,\text{land}}$ is available from the GTAP database (more on data for calibration in Appendix **??**). $\pi_i^{fk}$ and $Q_i^{fk}/Q_i^k$ can be calculated from the calibrated values of $r_i^k$ as explained in section 2.3. The chosen elasticity target leads to $\theta = 1.1$. For this calibration, the acreage elasticities of maize and soybean in the U.S. are 0.33 and 0.38, respectively, values that are comparable to recent estimates. The sensitivity of the results to the value of $\theta$ is assessed in section 5.2.

## 3.2 Data for initial equilibrium

Expressing the model in deviation from benchmark in section 2.3 allows us to identify the minimum set of information needed to calibrate the model. As with any general equilibrium model, we need aggregate value information at the country or sector level, such as final expenditures, trade flows, production values, and various budget shares. Information on potential yields under current climate and under climate change are taken from the GAEZ project (IIASA/FAO, 2012), which provides this information at the 5-arcminute level. Since this level of detail would result in a very large and difficult-to-solve model, we aggregate the yield information at the 1-degree level, which results in 11,801 fields, and test the effect of this aggregation in sensitivity analysis. Most agricultural statistics are taken from FAOSTAT, but we also need additional information not available in FAOSTAT datasets. We use Ramankutty and Foley (1999) for the extent of each field that is devoted to agricultural land. All other data comes from the GTAP database, in particular the value of livestock production and the share of land in production costs. Details about the various data and how they are combined are provided in Appendix **??**.

### 3.3 Ability to match observed land allocation

The calibration procedure imposes a perfect fit on all the data used for calibration. However, it does not rely on information about acreages, since these are predicted by the model using the producers' optimality conditions given country-level land rents and field-level potential yields (section 2.3). In consequence, it is possible to validate the combination of functional form assumptions and parameter values used to represent the model's supply-side by comparing the model-predicted land allocation with observations. For the observations, we use the country-level physical area from the SPAM database (IFPRI, 2019). SPAM physical areas do not correspond to official statistics, which do not exist on a systematic basis, but to harvested areas corrected using various sources for the occurrence of multiple harvests in a year. Thus, they are a natural counterpart to the areas predicted by the model.

To allow the comparison, we aggregate the 35 model crops as well as SPAM crops to a set of 26 common crops, a procedure which excludes some crops in the model (citrus fruits, grass, and olive) that cannot be mapped to SPAM crops. The two measures of acreages cannot be directly compared because they start from different values of total agricultural land in each country (and also a different base year, 2011 in the model and 2010 in SPAM). To make them comparable, the acreage shares in the model (normalized to the 26 common crops) are multiplied for each country by the total acreages of SPAM 26 crops. The model fit is displayed in the appendix (figure **??**). With a $R^2$ of 0.82, the fit is excellent (without the rescaling of total areas it is 0.73). Without using any information about acreages in the calibration, the model replicates this moment very well.

## 4 Quantitative results

### 4.1 Main counterfactual results

The main counterfactual consists in changing the potential yields, $A_i^{fk}$, from their values under current climate to their values at the 2080s horizon under climate change from the emission scenario A1FI. The welfare results are presented in table 4. Column 1 reports the share of crop output in GDP, which will prove useful to interpret welfare results as countries with a high share of GDP devoted to agriculture are more likely to be affected by changes in this sector. Column 2 reports the net agricultural trade as a share of the value of agricultural production ($[\sum_{k\in\mathcal{K}^a}(\sum_{j\in\mathcal{I}} X_{ij}^k - X_i^k)]/\sum_{k\in\mathcal{K}^a} p_i^k Q_i^k$). By measuring the direction of the dependence on foreign markets, this indicator helps interpret the changes in terms of trade. Columns 3 to 5 report welfare changes in percentage of GDP and its decomposition following equation (48) between terms-of-trade and productivity effects. The last nine lines report the average results for regional aggregates and for the world, with welfare calculated for the world (indexed $w$), and similarly for aggregates, as

$$\frac{EV_w}{E_w} = \frac{\sum_{j\in\mathcal{I}} EV_j}{E_w}. \tag{51}$$

Table 4: Benchmark counterfactual welfare results (welfare as % of GDP)

| | | | Welfare decomposition[b] | | | No adjustment on | | |
|---|---|---|---|---|---|---|---|---|
| Country[a] | Crop output as % of total GDP (1) | Net ag. trade as % of ag. prod (2) | Ag. terms of trade (3) | Productivity change (4) | Total (5) | acreage shares (6) | bilateral import shares (7) | export shares (8) |
| Argentina | 5.74 | 60.63 | 3.11 | 0.36 | 3.46 | 6.94 | 1.37 | 4.38 |
| Australia | 1.52 | 34.73 | 0.52 | −0.26 | 0.26 | 0.44 | 0.42 | 0.25 |
| Bangladesh | 12.28 | −31.46 | −4.96 | −4.34 | −9.31 | −11.63 | −13.32 | −10.55 |
| Brazil | 4.68 | 38.01 | 3.36 | −2.44 | 0.91 | 1.20 | 2.19 | 0.96 |
| Canada | 1.31 | 25.48 | −0.07 | 0.14 | 0.07 | 0.26 | −0.92 | 0.07 |
| China (including Hong Kong) | 6.47 | −4.91 | 0.04 | −0.68 | −0.65 | −2.93 | −0.98 | −0.62 |
| Colombia | 3.98 | 4.46 | 3.01 | −4.75 | −1.76 | −2.16 | −0.66 | −1.74 |
| Egypt | 5.35 | −48.12 | −2.13 | −2.04 | −4.17 | −5.67 | −4.00 | −4.62 |
| Ethiopia | 40.05 | 0.66 | 16.73 | −0.97 | 15.76 | 28.02 | −6.67 | 16.60 |
| France | 1.05 | 18.03 | 0.15 | −0.08 | 0.07 | −0.22 | −0.23 | 0.13 |
| Germany | 0.57 | −7.38 | −0.75 | 0.01 | −0.74 | −1.26 | −1.05 | −0.80 |
| Greece | 3.63 | −9.92 | −0.57 | −7.14 | −7.74 | −9.13 | −7.84 | −8.46 |
| India | 11.61 | 4.80 | 0.06 | −7.54 | −7.51 | −8.37 | −8.35 | −8.05 |
| Indonesia | 11.74 | −7.90 | 0.87 | −5.79 | −4.94 | −5.93 | −5.84 | −5.39 |
| Iran | 2.88 | −14.55 | −0.77 | −1.42 | −2.19 | −3.41 | −3.47 | −2.78 |
| Italy | 1.03 | −23.38 | −0.94 | −0.94 | −1.88 | −2.81 | −2.03 | −2.03 |
| Japan | 0.82 | −31.90 | −0.35 | −0.08 | −0.43 | −0.79 | −0.56 | −0.50 |
| Kazakhstan | 3.08 | −1.10 | −0.65 | −0.43 | −1.08 | −1.44 | −1.82 | −1.69 |
| Kenya | 18.01 | 4.81 | 12.90 | −3.52 | 9.38 | 11.60 | −8.88 | 6.36 |
| Korea, South | 1.17 | −48.79 | −0.90 | −0.06 | −0.96 | −1.68 | −1.29 | −1.12 |
| Malaysia | 7.62 | −30.07 | −4.81 | −0.66 | −5.47 | −7.36 | −6.07 | −5.98 |
| Mexico | 1.66 | −17.83 | 0.13 | −0.85 | −0.72 | −1.10 | −0.72 | −0.83 |
| Morocco | 5.43 | −27.36 | −2.75 | −4.97 | −7.74 | −9.58 | −8.25 | −8.66 |
| Netherlands | 0.47 | −15.93 | −3.32 | −0.01 | −3.33 | −4.97 | −4.18 | −3.39 |
| Nigeria | 9.97 | −9.98 | −0.77 | −13.76 | −14.59 | −16.32 | −19.17 | −15.36 |
| Pakistan | 9.08 | 1.86 | 0.27 | −1.73 | −1.46 | −2.50 | −2.33 | −1.15 |
| Peru | 3.35 | −6.51 | 1.53 | −2.70 | −1.19 | −2.18 | −1.31 | −1.26 |
| Philippines | 8.06 | −0.75 | 5.09 | −6.58 | −1.51 | 6.08 | −0.87 | −1.20 |
| Poland | 2.09 | 2.34 | −0.43 | 0.11 | −0.32 | −0.55 | −0.96 | −0.33 |
| Romania | 5.47 | −2.01 | −0.56 | −0.52 | −1.07 | −1.65 | −1.31 | −1.14 |
| Russia | 1.90 | −9.20 | −0.66 | −0.07 | −0.73 | −1.29 | −1.28 | −0.83 |
| Senegal | 7.45 | −45.21 | −6.01 | −5.69 | −11.71 | −16.88 | −18.23 | −15.87 |
| South Africa | 1.89 | 1.49 | 1.40 | −0.90 | 0.50 | 0.95 | −0.07 | 1.02 |
| Spain | 1.17 | 1.08 | 0.91 | −0.92 | −0.02 | −0.50 | 0.30 | 0.03 |
| Sri Lanka | 4.60 | −38.63 | −3.04 | −6.73 | −9.80 | −11.93 | −10.71 | −10.89 |
| Thailand | 6.67 | 20.50 | 0.49 | −4.44 | −3.96 | −5.34 | −4.02 | −5.79 |
| Turkey | 4.19 | −7.25 | 0.22 | −0.90 | −0.68 | −2.93 | −0.90 | −0.83 |
| Ukraine | 12.47 | 30.53 | 2.17 | −0.97 | 1.21 | 1.86 | 0.94 | 1.49 |
| United Kingdom | 0.47 | −37.96 | −0.52 | 0.01 | −0.51 | −0.86 | −0.73 | −0.61 |
| United States | 1.19 | 15.35 | −0.03 | −0.14 | −0.17 | −0.25 | −0.17 | −0.16 |
| Viet Nam | 16.60 | −1.78 | 2.39 | −9.59 | −7.24 | −8.35 | −6.60 | −8.68 |
| Asia | 5.26 | −5.95 | −0.14 | −1.58 | −1.73 | −2.97 | −2.12 | −1.90 |
| Commonwealth of Independent States | 3.38 | −1.69 | −0.56 | −0.14 | −0.70 | −1.19 | −1.28 | −0.81 |
| Europe | 0.94 | −5.14 | −0.51 | −0.29 | −0.80 | −1.40 | −1.12 | −0.85 |
| Latin America | 4.01 | 23.79 | 2.50 | −2.35 | 0.15 | 0.52 | 0.63 | 0.24 |
| Middle East and North Africa | 2.29 | −38.50 | −1.39 | −1.01 | −2.40 | −3.82 | −2.88 | −2.85 |
| Northern America | 1.21 | 16.58 | −0.04 | −0.11 | −0.15 | −0.19 | −0.25 | −0.13 |
| Oceania | 1.63 | 37.31 | 0.61 | −0.38 | 0.23 | 0.26 | 0.23 | 0.28 |
| Sub-Saharan Africa | 12.56 | −3.08 | 2.86 | −9.38 | −6.55 | −7.28 | −10.11 | −7.21 |
| World | 2.87 | 0 | 0 | −1.00 | −1.00 | −1.59 | −1.30 | −1.09 |

Notes: [a] Only countries represented individually in the model are presented here. [b] From equation (47), the sum of columns 3 and 4 gives approximately column 5. Decomposition obtained by dividing the yield shocks linearly in 800 shocks. It is almost exact for countries with limited welfare changes, but little discrepancies appear when absolute welfare changes exceed 10%.

The welfare decomposition shows us that few countries experience gains related to productivity changes (column 4), and if there are gains, they tend to be rather small, with a maximum of 0.36 for Argentina. But there are countries that can benefit a lot from climate change. In these cases, the welfare gains do not come from increased yields caused by climate change but from improvements in their agricultural terms of trade. This appears clearly for Argentina, Ethiopia, and Kenya. Because of the inelasticity of demand for food, the reduction in yields triggered by climate change requires large changes in prices to clear markets and, thus, large terms-of-trade effects. One implication is that the countries that initially export a large proportion of their agricultural production (e.g., Argentina, Brazil, Canada, France, Ukraine) tend to gain from climate change, even if they suffer from productivity losses, by shifting the burden of the adjustment to climate change to consuming countries through international prices. The opposite is also true: net-food-importing countries suffer from losses related to terms-of-trade. Overall, for half of our individual countries, the welfare impact of terms-of-trade effects is larger than the productivity impact.

Because of these various effects, food-importing, poor, tropical countries are particularly vulnerable to climate change. Their high share of crops in GDP makes them more economically sensitive to yield shocks. Their reliance on imports exposes them to detrimental terms-of-trade shocks. And their geographical location is the most exposed to the negative effects of climate change on yields. Bangladesh, Malaysia, and Sri Lanka are examples of this in the model.

We turn now to the specific situation of Sub-Saharan Africa, the region experiencing the largest losses, with an average loss of $-6.55\%$. One obvious explanation for this large welfare loss is the large decrease in potential yields on some of key African crops such as cocoa and tropical roots, combined with the high share of agriculture in GDP in these countries. But there is a complementary explanation. A specificity of African agriculture is its reliance on crops that are scarcely traded (and sometimes not at all according to official statistics), such as tropical roots (cassava, sweet potatoes, and yams) and tropical cereals (millet and sorghum), because of perishability or because of the high trade costs in the region (Porteous, 2019). For example, starchy roots contribute to 23% of Nigerian caloric intake with almost no international trade. When the productivity of such a crop is severely hit by climate change, the model leaves little scope for adaptation. Without initial trade, no trade can be created under an Armington structure. Because of the low flexibility of demand, domestic prices increase dramatically, driving up the planted areas despite the lower productivity, which aggravates the severity of the initial shock as more resources are pulled into producing a crop that now requires relatively much more land to produce than before. Things would have played out differently with enough initial trade: acreage in tropical roots would have been reduced, and the country would have specialized in other production and relied more on imports. With large welfare gains, Ethiopia and Kenya are two exceptions in Sub-Saharan Africa. This is also visible in figure **??** that represents the changes in aggregate potential yields where these countries are part of the small African regions experiencing yield gains on average. For the other African countries, the lack of international trade aggravates the productivity loss by preventing reallocations to more profitable crops (this claim is proved in section 5.3).

To illustrate the role of international trade in allowing large adjustments to climate change between countries, figure 1 plots the changes caused by climate change in the export shares in total trade of the main cereals, maize, rice, and wheat. Traded quantities vary with climate change with increases in import volume of 7%, 38%, and 8% respectively for maize, rice, and wheat. Shares in world trade vary equally. Shares of maize and rice in particular bear little resemblance to their current market shares. For the maize market, traditional exporters such as the U.S., Brazil, France, and Ukraine suffer strong yield reduction and consequentially reduce their exports. Canada, Germany, and China, located in northern latitudes, have higher maize yields. They step in to fill the gap, with the world production of maize even increasing by 8%. The effects are similar for rice. The traditional rice exporters are tropical countries that are severely hit by climate change. Rice production moves north, and new exporters emerge: China, Korea, and Japan. The export shares in the wheat market change less with decreases in some traditional exporters (Argentina, Australia, France, United States) and increases in others, located in northern latitudes (Canada, Germany, Russia). These results show that pattern of international trade flows in agricultural products may look extremely different from now because of the effects of climate change.

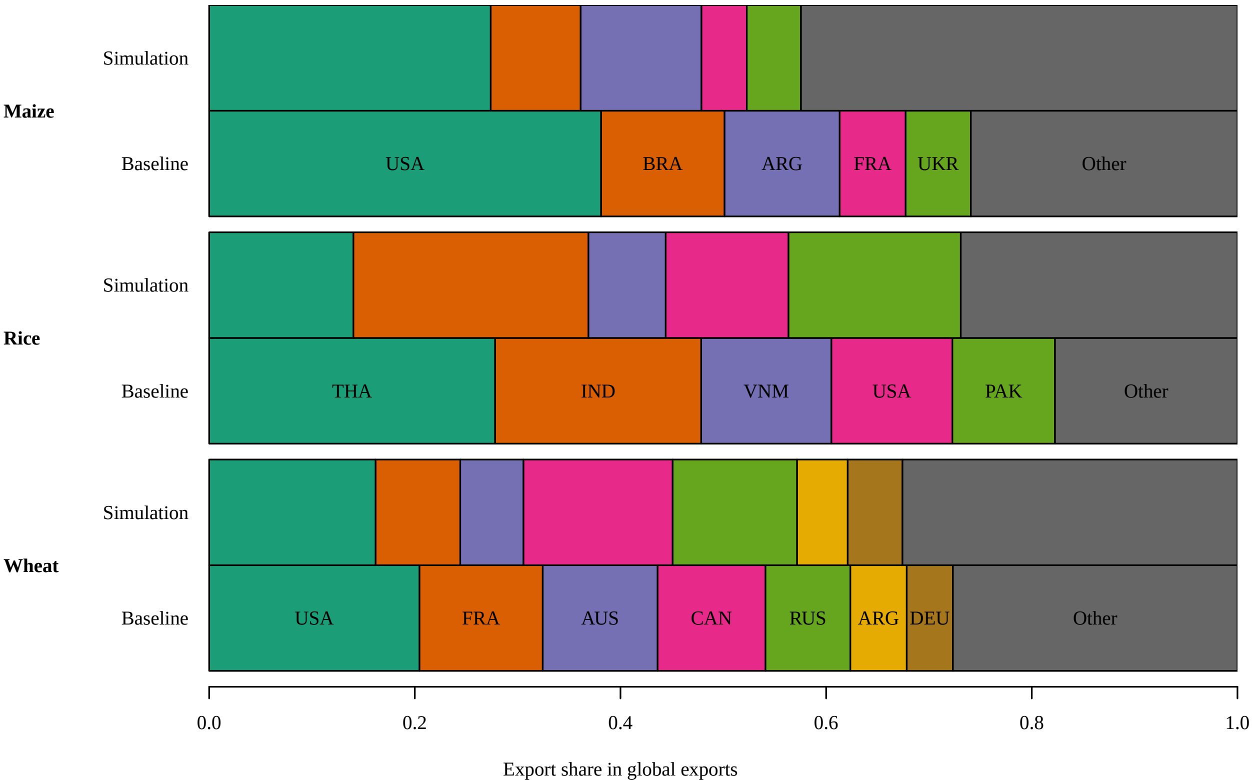

Figure 1: Changes in export shares

## 4.2 The role of acreage adjustments

To assess the role of acreage changes in adaptation to climate change, we follow CDS and consider a scenario where acreages cannot adjust and are fixed to their initial values. In this case, the counterfactual production is given by

$$Q_i^{k\prime} = \sum_{f \in \mathcal{F}_i} s_i^f \pi_i^{fk} \operatorname{E}\left[ A_i^{fk\prime}(\omega) \,|\, r_i^k A_i^{fk}(\omega) \in \arg\max_{l \in \mathcal{K}^c} r_i^l A_i^{fl}(\omega) \right], \tag{52}$$

which using that $A_i^{fk\prime}(\omega) = A_i^{fk}(\omega)\, A_i^{fk\prime}/A_i^{fk}$ gives

$$Q_i^{k\prime} = \sum_{f \in \mathcal{F}_i} s_i^f A_i^{fk\prime} \left(\pi_i^{fk}\right)^{(\theta-1)/\theta}, \tag{53}$$

and in exact hat algebra

$$\hat{Q}_i^k = \sum_{f \in \mathcal{F}_i} \hat{A}_i^{fk} \frac{Q_i^{fk}}{Q_i^k}. \tag{54}$$

This counterfactual where acreage shares stay the same is presented in column 6 of table 4. At the world level, preventing adjustments on production increases the initial welfare losses by 59%. This constraint does not reverse the sign of most welfare results, it just amplifies them. Countries that tend to gain from climate change without the constraint tend to gain more with it, and vice versa for countries that tend to lose from climate change. Since gains are mostly related to terms-of-trade gains, this result implies that preventing supply adjustments from occurring exacerbates the terms-of-trade change for the benefits of the net-food-exporting countries.

## 4.3 The role of trade adjustments

We turn now to analyzing the role that adjustments to international trade patterns may play in alleviating the consequences of climate change. In contrast with the role of acreages changes that can be captured by simply fixing the initial acreages, there are two difficulties in analyzing the role of trade changes. First, it is not possible to fix trade flows to their initial values, given that these trade flows could not be satisfied in the case of strong yield reductions. Second, there are various ways in which trade adjusts, so there are various legitimate counterfactual exercises to capture the role of its adjustments. In this paper, we use two different approaches to analyze the role of trade, each corresponding to a different adjustment margin.[10]

Our first approach to restrict trade adjustments is to fix the bilateral import (value) shares to their initial values. Given the model Armington structure, fixing the bilateral trade shares is symmetric to what is done for land by fixing the acreage shares. This approach focuses on the potential need for importing countries to reallocate trade flows between different import sources because climate change may affect countries' comparative advantages. This is done by simply replacing the gravity equation (41) with $\hat{X}_{ij}^k = \hat{X}_j^k$.

Our second approach fixes the shares of exports for agricultural goods to their initial values, as is done in CDS. This approach focuses on the potential changes in the role of exporting countries caused by the changes in their potential yields relative to the rest of the world. This is imposed by the following equation that states that changes in domestic trade are proportional to changes in domestic production:

$$\hat{X}_{ii}^k / \hat{p}_i^k = \hat{Q}_i^k \text{ for all } k \in \mathcal{K}^a. \tag{55}$$

This equation holds by adding ad-valorem export taxes (or subsidies), denoted $\delta_i^k$, to the model. Three of the model equations must be adjusted accordingly: equation (39) that defines the consumer price index,

$$\hat{P}_j^k = \left[\sum_{i\in\mathcal{I}} \alpha_{ij}^k \left(\hat{\delta}_i^k \hat{p}_i^k\right)^{1-\sigma}\right]^{1/(1-\sigma)}; \tag{56}$$

equation (41) that defines bilateral imports,

$$\hat{X}_{ij}^k = \left(\hat{\delta}_i^k \hat{p}_i^k / \hat{P}_j^k\right)^{1-\sigma} \hat{X}_j^k; \tag{57}$$

and equation (43) that defines the representative agents' budget constraint and where the tax revenues now appear as a lump sum transfer,

$$E_i \hat{E}_i = A_i^0 N_i + \sum_{k\in\mathcal{K}^c} R_i^k \hat{r}_i^k \hat{Q}_i^k + \sum_{k\in\mathcal{K}^a, j\in\mathcal{I}, j\neq i} \left(\hat{\delta}_i^k - 1\right) \frac{X_{ij}^k \hat{X}_{ij}^k}{\hat{\delta}_i^k}. \tag{58}$$

The welfare results when trade adjustments are limited are presented in columns 7 and 8 of table 4. The two constraints lead to very different welfare results, with much larger welfare losses in column 7, where bilateral import

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[10] See also Randhir and Hertel (2000), Baldos and Hertel (2015), and Janssens et al. (2020) for different choices of counterfactual for analyzing the role of trade adjustments in relation to climate change.

shares are fixed to their initial values, than in column 8, where welfare results are much closer to the benchmark results. The results in column 8 suggest that the exported share is not an important margin of adjustment to climate change, while the results in column 7 suggest that importing countries will have to significantly change their import sources to limit their welfare losses. We postpone the detailed comparison of the two approaches to section 5.3. Until this comparison, we present both measures of the role of trade, but given the limited effect of fixing the export shares, we privilege the scenario that fixes the bilateral import shares for comparison with the role of acreage changes. The role of bilateral import share adjustments in adaptation to climate change, as measured in column 7, is smaller than the role of acreage adjustments but also much more heterogeneous. For example, trade adjustments play a much bigger role for Sub-Saharan Africa than acreage adjustments.

## 4.4 Aggregate yield shocks

To better understand how changes in potential yields affect acreages, trade, and welfare, we decompose the yield shocks into different components and apply them separately. We start by applying the average global change in potential yields to each field. To be able to average yield shocks from different crops, we need a weighting scheme. We use the welfare metric and calculate the average shock by weighting each field-level shock by its first-order welfare contribution: $\hat{A} = \sum_{i\in\mathcal{I}, f\in\mathcal{F}_i, k\in\mathcal{K}^c} r_i^k Q_i^{fk} \hat{A}_i^{fk} / \sum_{i\in\mathcal{I}, f\in\mathcal{F}_i, k\in\mathcal{K}^c} r_i^k Q_i^{fk}$. Calculated in this way, the global average yield shock due to climate change is $-13.2\%$. The new counterfactual potential yields are then calculated as

$$A_i^{fk\prime} = \hat{A} A_i^{fk}. \tag{59}$$

The other counterfactual simulations with aggregate shocks are for the average yield shocks at the country level, at the crop level, and at the country-crop level, with the averages calculated as above. Table 5 reports the results of these simulations.

Table 5: Results under various counterfactual aggregate yield shocks (percentage change)

| Variable | World average (1) | Country average (2) | Crop average (3) | Country-crop average (4) | Benchmark without new crop on fields (5) | Benchmark (6) |
|---|---|---|---|---|---|---|
| Welfare change | | | | | | |
| Asia | −0.52 | −0.46 | −1.86 | −2.75 | −2.60 | −1.73 |
| Commonwealth of Independent States | −0.10 | −0.06 | −1.88 | −1.08 | −1.01 | −0.70 |
| Europe | −0.14 | −0.26 | −1.35 | −1.28 | −1.22 | −0.80 |
| Latin America | 0.40 | −0.04 | 1.24 | 0.47 | 0.47 | 0.15 |
| Middle East and North Africa | −0.70 | −1.17 | −3.20 | −3.55 | −3.39 | −2.40 |
| Northern America | 0.10 | 0.10 | −0.15 | −0.15 | −0.15 | −0.15 |
| Oceania | 0.30 | 0.31 | 0.08 | 0.29 | 0.28 | 0.23 |
| Sub-Saharan Africa | −0.56 | −3.52 | −5.59 | −7.00 | −6.94 | −6.55 |
| World | −0.17 | −0.31 | −1.16 | −1.47 | −1.40 | −1.00 |
| World - No acreage shares adjustment | −0.18 | −0.32 | −1.25 | −1.58 | −1.59 | −1.59 |
| World - No bilateral import shares adjustment | −0.17 | −0.37 | −1.17 | −1.76 | −1.73 | −1.30 |
| World - No export shares adjustment | −0.17 | −0.33 | −1.17 | −1.54 | −1.47 | −1.09 |
| MAD of acreage shares | 20.66 | 26.29 | 41.81 | 43.24 | 60.62 | 64.12 |
| MAD of between-country acreage shares | 19.79 | 25.47 | 39.63 | 41.16 | 31.39 | 38.91 |
| MAD of international trade volumes | 13.43 | 42.68 | 39.15 | 59.78 | 60.38 | 70.31 |

This way of aggregating yields shocks present two limits that should be understood. First, since the weights used to aggregate yield shocks are based on a first-order approximation based on the baseline equilibrium values, they do not account for the fact that the economic weight of each crop and each field changes with climate change. Second, since equation (59) is multiplicative in the initial yields, it cannot account for pairs field-crop where productivity was initially zero and becomes positive after climate change. To make things comparable, table 5 reports the benchmark results in column 6 but also the benchmark where this extensive margin is shut down in column 5. Comparing the last two columns shows that allowing new crops in fields has a huge impact and appears as a crucial margin of adaptation to climate change. Climate change will reduce the productivity in many fields but will also make new production possible, reducing global welfare losses by more than one quarter.

To save on space, welfare results are reported for regional aggregates (defined in table **??**). The amount of change in acreages and in trade flows is assessed using measures of mean absolute deviation (MAD), reported in the last three rows. For acreages, it is calculated on acreage shares weighted by initial areas:

$$\text{MAD of acreage shares} = \frac{\sum_{i\in\mathcal{I}, f\in\mathcal{F}_i, k\in\mathcal{K}^c} s_i^f \pi_i^{fk} \left|\hat{\pi}_i^{fk} - 1\right|}{\sum_{i\in\mathcal{I}, f\in\mathcal{F}_i, k\in\mathcal{K}^c} s_i^f \pi_i^{fk}}. \tag{60}$$

It represents the average absolute percentage change in crop acreages. Another interesting measure of changes in acreages is the between-country changes that consider only the acreage changes aggregated at the country-level:

$$\text{MAD of between-country acreage shares} = \frac{\sum_{i\in\mathcal{I}, k\in\mathcal{K}^c} \left(\sum_{f\in\mathcal{F}_i} s_i^f \pi_i^{fk}\right) \left|\hat{\pi}_i^{k} - 1\right|}{\sum_{i\in\mathcal{I}, f\in\mathcal{F}_i, k\in\mathcal{K}^c} s_i^f \pi_i^{fk}}, \tag{61}$$

with $\pi_i^k \equiv \sum_{f\in\mathcal{F}_i} s_i^f \pi_i^{fk} / \sum_{f\in\mathcal{F}_i} s_i^f$. For trade flows, we weight the change in the volume of trade by the initial trade value:

$$\text{MAD of international trade volumes} = \frac{\sum_{i,j\in\mathcal{I}, i\neq j, k\in\mathcal{K}^c} X_{ij}^k \left|\hat{X}_{ij}^k / \hat{p}_i^k - 1\right|}{\sum_{i,j\in\mathcal{I}, i\neq j, k\in\mathcal{K}^c} X_{ij}^k}. \tag{62}$$

It represents the average absolute percentage change in trade volumes.

From column 1 to 5, the world is exposed to the same aggregate yield shock, but the shock is applied differently across the columns. Depending on how the yield shock is applied, it has dramatically different effects. If the shock is uniform across countries, the global welfare losses are the lowest. Under this configuration, climate change is much less costly for countries from the Middle East, North Africa, and Sub-Saharan Africa, while results are weakly changed for Latin America and Oceania. Despite a uniformly negative shock, the two regions that win from climate change in the benchmark still win because of their terms-of-trade gains. Because the shock is the same, prices tend to move similarly everywhere, which induces much less trade change than in other scenarios. In this scenario, there is almost no role for acreage or trade adjustments: welfare losses are almost the same whether these margins are active or not, which is consistent with the fact that this aggregate shock creates little change in relative prices and so little change in acreage and trade.

In the second column, the shock is specific to each country and therefore affects the countries' comparative advantages in crop production. One mechanism explains the higher welfare losses compared to a uniform shock. The shock now affects countries differentially, but countries do not have the same capacity to adapt to the shock. In this model, one of the key adaptation mechanisms is international trade. From equation (39), the change in consumer prices is a power mean of import prices weighted by initial trade shares. If the initial trade shares (excluding trade to self) are small, the consumer price is very dependent on the domestic producer price, which increases sharply in the case of adverse shock if there are no exports to reduce. Sub-Saharan Africa is both exposed to a larger shock than the mean and is less connected through international trade so less able to adapt to the shock, which aggravates the mean effect. In this setting, there is no shock heterogeneity within a country between crops and fields, so acreage adjustments do not matter, but trade adjustments do.

In column 3, the shock is specific to each crop but affects countries similarly. So, it affects the countries' comparative advantages only because their initial crop specialization differs. This creates slightly fewer trade opportunities than a country-specific shock given that a crop is affected uniformly everywhere, but it leads to more acreage reallocations. The same mechanism operates to explain the different welfare gains: some crops tend to create more welfare losses than others because of the lack of adaptation through trade.

Column 4 of table 5 reports the results when the average country-crop shock is applied for each couple field-crop. This shock is closer to the benchmark climate change shock than either of the three previous scenarios. This shock is also similar to what would be obtained with a model with one field per country (and so to the early literature on the topic), since it neglects all within-country changes. In this case, comparative advantages change between countries and for all crops, but without within-country differentiation, outside of the initial field heterogeneity. This is the scenario with the highest global welfare loss, higher even than in the benchmark without new crops. Comparing the last rows of columns 4 and 5 shows that having shocks that are heterogeneous within countries affects the amount of change in international trade volumes little, consistent with the idea that countries should have the same comparative advantages between the two columns. In column 5, more adjustments take place on the supply side, with much more change in acreages allowed by the within-country heterogeneity.

In the absence of within-country heterogeneity in the climate-change shock (columns 1–4), the acreage adjustments take place mostly between countries, with negligible within-country adjustments, and the role of acreage adjustments is small. With within-country shock heterogeneity (columns 5–6), the share of within-country adjustments increases to close to one-third. Common to all the scenarios without within-country heterogeneity is the fact that they neglect the possibility of planting new crops on fields. For a better comparison with the benchmark, the benchmark simulation without this possibility of planting new crops is presented in column 5 and shows a crucial result. Preventing new crops from being planted increases the welfare losses of climate change by 40% with respect to the benchmark. Going one step further and preventing all acreage adjustment increases the losses further but by less than preventing new crops. This shows that the most important part of the supply-side adaptation to climate change is the possibility of planting crops that could not grow before climate change. Adjusting the acreages within the set of crops that can be grown initially has a much smaller effect.

# 5 Sensitivity to the behavioral assumptions

In this section, we analyze how our behavioral assumptions affect our conclusions about the respective role of acreage and trade adjustments. We do this by varying the flexibility of each adjustment margin, which clarifies the inner workings of the model and the mechanisms that trigger more or less of a role for international trade adjustments. At the end of this section, we also try to clarify what drives the differences between this paper's and CDS' conclusions by parameterizing the model with local behaviors as close as possible to those used in CDS. The various models are presented in table 6. For comparison, the last row displays CDS' benchmark results. When interpreting the results of this sensitivity analysis, four effects must be distinguished: the change in the welfare cost of climate change (column 1), the change in the role of production adjustments (comparing column 2 to 1), the change in the role of trade adjustments (comparing columns 3 or 4 to 1), and the change in the relative benefits of trade versus production adjustments (comparing columns 3 or 4 to 2).

Table 6: Role of each adjustment margins in welfare changes (as % of world GDP)

| | | No adjustment on | | |
|---|---|---|---|---|
| Model | Full adjustment (1) | acreage shares (2) | bilateral import shares (3) | export shares (4) |
| 1. Benchmark calibration ($\epsilon = 0.5, \kappa = 0.6, \varsigma = 0.9, \theta = 1.1, \eta = 0, \sigma = 5.4$) | −1.00 | −1.59 | −1.30 | −1.09 |
| 2. Benchmark calibration – 5-arcminute modeling | −0.94 | −1.72 | −1.21 | −1.02 |
| 3. $\epsilon = 0.2$ | −1.72 | −3.71 | −3.02 | −2.17 |
| 4. $\epsilon = 1$ | −0.74 | −1.12 | −0.89 | −0.78 |
| 5. $\kappa = 0.4$ | −1.67 | −3.27 | −2.41 | −1.89 |
| 6. $\kappa = 1.2$ | −0.51 | −0.73 | −0.64 | −0.54 |
| 7. $\kappa = 2.82$ | −0.27 | −0.42 | −0.35 | −0.29 |
| 8. $\varsigma = 0.6$ | −1.03 | −1.63 | −1.43 | −1.12 |
| 9. $\varsigma = 1.8$ | −0.95 | −1.53 | −1.28 | −1.04 |
| 10. $\varsigma = 2.82$ | −0.93 | −1.50 | −1.24 | −1.01 |
| 11. $\theta = 1.05$ | −1.06 | −1.58 | −1.44 | −1.15 |
| 12. $\theta = 1.2$ | −0.91 | −1.61 | −1.19 | −0.99 |
| 13. $\eta = 0.02$ | −0.94 | −1.48 | −1.17 | −1.03 |
| 14. $\eta = 0.04$ | −0.89 | −1.38 | −1.10 | −0.97 |
| 15. $\eta = 0.06$ | −0.84 | −1.30 | −1.04 | −0.92 |
| 16. $\sigma = 3$ | −1.15 | −1.75 | −1.35 | −1.20 |
| 17. $\sigma = 10$ | −0.85 | −1.45 | −1.20 | −0.99 |
| 18. $\kappa = \varsigma = 2.82$ | −0.24 | −0.38 | −0.30 | −0.25 |
| 19. $\epsilon = 1, \kappa = \varsigma = 2.82$ | −0.21 | −0.31 | −0.25 | −0.22 |
| 20. $\theta = 1.2407$ | −0.88 | −1.62 | −1.15 | −0.96 |
| 21. $\epsilon = 1, \kappa = \varsigma = 2.82, \theta = 1.2407$ | −0.20 | −0.32 | −0.23 | −0.20 |
| 22. $\epsilon = 1, \kappa = \varsigma = 2.82, \theta = 1.2407$ – 5-arcminute modeling | −0.19 | −0.35 | −0.22 | −0.20 |
| Costinot et al. (2016) benchmark results | −0.26 | −0.78 | – | −0.27 |

Notes: $\epsilon$ is the price elasticity of demand for the bundle of agricultural goods, $\kappa$ is elasticity of substitution between agricultural products for final demand, $\varsigma$ is the elasticity of substitution between agricultural products for feed demand, $\theta$ is shape parameter of the Fréchet distribution used for crop yields, $\eta$ is the elasticity of crop output to the input of the non-agricultural good, and $\sigma$ is the elasticity of substitution between varieties.

## 5.1 Demand

**Price elasticity of agricultural good demand** To understand the role of the price elasticity of agricultural good demand, we repeat the counterfactual analysis with different values. We consider an elasticity $\epsilon$ of 0.2 in model 3, a value close to what is found by Comin et al. (forthcoming) for the U.S. using household expenditure data and for OECD countries in cross-country estimations. In model 4, we consider an elasticity of 1, a value that, following Comin et al.'s estimates and the structural change literature, should be considered an upper bound.

Welfare losses increase with a more inelastic demand, and vice versa. However, these changes in welfare results are not straightforward to interpret, as expected when preferences and behaviors are changed simultaneously. With a more elastic demand as in model 4, the contribution of changes in acreages decreases. Instead of increasing the global welfare losses in the benchmark by 59%, losses increase by 51% if $\epsilon = 1$. The effect is similar if considering the counterfactual where bilateral import shares are fixed: the role of import shares in adaptation to climate change decreases, but the contribution of import shares to adaptation relative to the contribution of acreage adjustments stays the same. This result proceeds from a simple intuition: a more elastic demand reduces the size of the price adjustments, so it reduces the adaptive role of both the supply and trade margins that are triggered by changes in relative prices.

**Final demand elasticity of substitution between agricultural products** In our baseline model, the elasticity of substitution between agricultural products for food is calibrated at 0.6, consistent with the widespread estimations of inelastic demand for food products. While the literature on food demand mentioned in section 3.1 robustly finds inelastic food demand with elasticities that rarely exceed 1 in absolute value, this literature is mostly concerned with short-run elasticities, even if short run is understood as annual. When considering the effects of climate change and neglecting the transitional dynamics to the 2080s, we are interested in long-run elasticities, but to our knowledge, these have not been studied. In two papers, Atkin (2013, 2016) touches on this issue by showing that food demand is affected by habit formation and how habits could affect the nutritional effects of trade liberalization and migration. Tastes for certain foods evolve depending on how much they were consumed in the past, especially as a child, and therefore depending on their past prices. This mechanism would point toward higher demand elasticities in the long run than in the short run as tastes gradually evolve toward the foods that are the cheapest locally. However, Atkin (2013) also notes that tastes evolve slowly, with a doubling in the price of a staple a decade earlier reducing the budget share of that food by just 3 to 5%. This slow adjustment is in the context of poor Indian households that could be expected to have higher food demand elasticities, and thus a higher propensity to tastes adjustment, than affluent households in rich countries where the budget share of primary products is small.

To explore the quantitative importance of this possibility of a higher long-run substitution between food products, we consider a scenario with an elasticity of substitution of 1.2 in model 6, the double of the benchmark value. We also report the results with an elasticity lower than benchmark (model 5) and with the elasticity used in CDS: 2.82 (model 7). This substitution elasticity plays a key role in determining the size of the welfare losses with an order of magnitude between the smallest and the highest losses. Climate change is much less costly with more substitution between food products, since not all food products are affected alike and some even show higher potential yields under climate change, allowing the consumption to reallocate to cheaper products. This parameter also influences the respective role of changes in acreage and in ~~trade~~bilateral import shares, but without a clear pattern: decreasing the role of ~~trade~~ import shares adjustment for a lower elasticity, increasing it for double the benchmark elasticity, and returning to close to 80% of the effect of acreage adjustments for $\kappa = 2.82$.

**Feed demand elasticity of substitution between agricultural products** The literature on feed demand elasticities is limited and displays a lot of variations from −0.05 to −2.13 according to the papers reviewed previously. Since demand for feed is unlikely to be as inelastic as food demand, we use the elasticity of substitution between agricultural products for final demand as a lower bound in the sensitivity analysis. For the upper bound, we consider the double of the benchmark elasticity, which would put the feed demand elasticities in the high end of the literature. We also consider the substitution elasticity used for final demand in CDS: 2.82. Models 8–10 of table 6 report the results for these alternative values. As expected, a more elastic demand for feed implies less welfare loss. However, this effect is much lower than for final demand, despite a large share of 31% of feed demand in total demand for crops. This lower effect stems from the fact that the demand for feed is concentrated into far fewer crops than the demand for food (e.g., in the U.S., grass, maize, and soybean represent 80% of feed demand), which greatly decreases the opportunity for substitution. All these alternative values of elasticity tend to slightly increase the role of ~~trade~~ import shares adjustments.

## 5.2 Supply

**Acreage choice** We vary the acreage elasticity around its benchmark value, halving and doubling it. Since the acreage elasticity is proportional to $\theta - 1$, halving it decreases $\theta$ to 1.05 and doubling it increases $\theta$ to 1.2. Corresponding to these values, the acreage elasticity of maize and soybean in the U.S. are 0.17 and 0.19 for the lower $\theta$ and 0.66 and 0.75

for the higher $\theta$. When the value of $\theta$ is changed, the calibration of the initial rents should be done for the new value according to equation (44). The aggregate values of production, trade, and final demand stay the same, but a different $\theta$ implies slightly different initial land rents and thus different field acreages.

Models 11 and 12 of table 6 report the results of this exercise. Varying the degree of within-field heterogeneity from 1.05 to 1.2 influences welfare changes, with lower aggregate losses for a higher $\theta$. Despite the large variations that it implies in the supply elasticities, the welfare changes remain modest compared to the fact that welfare losses more than double if acreage shares are forced to stay the same. This is explained by what was discussed in section 4.4: the largest contribution to production adjustments comes from the possibility of planting new crops on fields, which is not affected by $\theta$. Despite limited welfare effects under full adjustment, $\theta$ affects the respective role of acreage and trade adjustments. With $\theta = 1.2$, there are more acreage adjustments in the full adjustment setup, which decreases the welfare losses and increase the contribution of acreage adjustments. The balance between acreage and ~~trade~~ import shares adjustments is also affected: with a lower $\theta$, their contribution is close, while with a higher $\theta$, acreage adjustments contribute much more to adaptation, although the contribution of ~~trade~~ import shares adjustments remains substantial. This points to some substitution between these two margins of adjustment: if one is more flexible, it decreases the need for the other. The less flexible domestic supply is, the wider the imbalances between domestic supply and demand are, which would call for more international trade to reduce the imbalances.

**Yield elasticity** For the sake of parsimony and because of the difficulty of obtaining reliable estimates of yield elasticities, we have assumed inelastic yields in the benchmark model. However, in addition to changing acreages, intensifying crop production could be a strategy to adapt to climate change. The increase in agricultural prices caused by climate change could make increasing inputs used for crop production profitable. Such a reaction is likely to be heterogeneous across fields, countries, and crops, depending on the existing gaps with respect to maximum yields, among other things. For this sensitivity analysis, we abstract from this complexity by assuming that yields can be expressed as isoelastic functions of input levels (the outside good being used as input), using the same elasticity $\eta$ for all crops and all countries. Appendix **??** details the changes to be made to the model to accommodate elastic yields. The model with elastic yields nests the benchmark model when yields are assumed to be inelastic, which corresponds to $\eta = 0$. Having elastic yields decreases the acreage elasticities for the same $\theta$. So, to maintain the same elasticities as in the benchmark model, the degree of within-field heterogeneity is taken equal to $\tilde{\theta} = \theta + \eta/(1-\eta)$, where $\theta$ is the benchmark value.

The debates about the indirect land-use changes caused by biofuel policies revolved a lot around the price elasticity of yields, since more elastic yields imply less land-use changes and consequentially less carbon emissions from planting crops on new lands. Berry (2011) and Berry and Schlenker (2011) argue that GTAP-based models use too large of yield-price elasticities, and that credible estimates are often not significant. Based on their review and some IV estimations, they consider that these elasticities should not exceed 0.1 for the main U.S. crops. Recent estimates in Scott (2013) and Haile et al. (2016) confirm this order of magnitude, while Miao et al. (2016) find a non-significant yield-price elasticity for U.S. soybean and an elasticity around 0.25 for U.S. maize, 0.25 also being the high value used in GTAP models and criticized by Berry (2011). Models 13–15 of table 6 report the counterfactual results with elastic yields assuming $\eta = 0.02$, 0.04, and 0.06, which correspond to yield-price elasticities for U.S. maize of 0.11, 0.21, and 0.33. With $\eta = 0.06$, model 15 corresponds to a situation where the yield-price elasticities are not far from the acreage-price elasticities, an extreme calibration according to this literature. Having elastic yields increases the total supply elasticity and, thus, the extent of supply-side adaptations, reducing welfare losses and the potential adaptive role of acreage and trade adjustments without affecting their relative contribution.

**Degree of spatial aggregation** Data on potential yields are available at the 5-arcminute level~~, the level at which CDS model is built~~. In this paper for reducing the computational burden of solving the model, we have aggregated the potential yields information to the 1-degree level. This significantly reduces the number of fields to account for, but it also reduces the spatial heterogeneity and the corresponding possibility to reallocate crops between fields. It is important to verify that this assumption ~~is not behind the results that trade matters for adaption by decreasing the~~ does not drive the results regarding the respective share of each adjustment margin by limiting supply-side adaptation ~~margin~~possibilities. One hint that the spatial aggregation may bias the results is provided in column 4 of table 5. In the limit, if fields are aggregated to one per country and all within-country heterogeneity is neglected, the role of acreage adjustments decreases greatly, becoming inferior to the role of ~~trade~~ import shares adjustments.

To verify the role of this specification, we solve the model at the 5-arcminute level for two calibrations: the benchmark calibration and the closest calibration to CDS (see section 5.4 for details). The results are available in models 2 and 22 and can be compared to models 1 and 21 that have the same calibrations. For CDS calibration, the difference is very small, but for the benchmark calibration, keeping as much spatial detail as possible matters. With more spatial heterogeneity, there are more supply-side adjustments, which decreases welfare losses and increases the role of acreage changes. The role of ~~trade~~ import shares adjustments also decreases but remains sizable. From this exercise, we can conclude that a setting with more detailed spatial information is important to capture the extent of supply-side adjustments better. However, for the purpose of this paper, yields are sufficiently spatially correlated that an aggregation at the 1-degree level is unlikely to reverse the paper's conclusions.

## 5.3 International trade

To better understand the role of trade adjustments, we consider three alternative models. First, we consider two models with different Armington elasticities: one with a value of 10, as estimated in Caliendo and Parro (2015) for agricultural products, and one with a value of 3, corresponding to some of our estimations in tables **??** and **??**. Second, we consider a situation of integrated world markets, which can be considered as an upper bound of what international trade can contribute to adaptation to climate change, because it amounts to neglecting all trade costs and preferences for varieties associated with countries of origin. This situation reflects the reality that many agricultural products are actually commodities with very little differentiation regarding what is produced between countries. In such a case, which is not relevant for all agricultural products (e.g., livestock), the Armington assumption we have adopted for convenience may be unduly restrictive, and the hypothesis of homogeneous goods would be more appropriate (as adopted for crops by Bergquist et al., 2019, and Sotelo, 2020). Properly modeling international trade in homogeneous goods is costly because of the need for extensive data on trade costs and the accounting in the model for all possible trade flows, even if initially null. So, we adopt the hypothesis of integrated world markets without trade costs, which simplifies the modeling of homogeneous products for this exercise and provides an upper bound for a model with trade costs. All products are assumed perfectly integrated, except grass, which remains non-tradable (but its price is pinned down in each country by the world price of livestock).

The changes to be made to the model to transform it to a model with integrated world markets are relatively simple: bilateral trade variables ($X_{ij}^k$) are removed as they are now irrelevant, consumer prices and producer prices are equal ($P_i^k = p_i^k = p^k$), and market clearing equations for consumer prices (40) and producer prices (42) are collapsed and summed over all countries. Only one model change is less obvious. Because of the Armington assumption, in the benchmark model, a crop is always produced in a country as long as there are positive potential yields. This is no longer the case if products are assumed homogeneous, so we need to account for the possibility of some land rents (and thus some production) being zero under climate change but positive in the baseline. This is done by expressing equation (32) for crops as a complementarity slackness condition:

$$\hat{r}_i^k \geq 0 \perp \hat{r}_i^k \geq \left(\hat{p}^k - \phi_i^{k,\text{labor}}\right)/\phi_i^{k,\text{land}}. \tag{63}$$

Changes in land rents completely follow changes in the corresponding world prices. We allow for the possibility of a land rent becoming zero in the counterfactual but not for the opposite situation of a land rent becoming positive after being zero. Because of equation (63), the model with integrated world markets is solved numerically as a mixed complementarity problem using the solver PATH.

Models 16 and 17 of table 6 report the results with lower and higher Armington elasticities. With less (more) elastic trade, there are less (more) trade reallocations under full adjustments and higher (lower) welfare losses. The adaptive roles of acreage and trade increase (decline) accordingly. This parameter logically affects their respective role with a lower (larger) role for trade with a lower (higher) elasticity. But even in the unfavorable case of $\sigma = 3$, preventing ~~trade~~ import shares adjustments still increases welfare losses by 17%. For the integrated world markets, we report only the results under full adjustment in column 1 of table 7. If all markets except grass are integrated, global welfare losses are halved, falling from 1% to 0.47%. The effect is especially strong for Sub-Saharan Africa, which benefits from climate change (+0.12% welfare) instead of a 6.55% loss. This demonstrates that one of the main reasons for the large welfare losses in Africa in the benchmark model is the low tradability of some of its key agricultural commodities (roots or coarse grains) combined with Africa's high trade costs.

Table 7: Effects of the assumptions about international trade (percentage change)

| Variable | Integrated world markets (1) | $\sigma = 10$ (2) | Benchmark $\sigma = 5.4$ (3) | $\sigma = 3$ (4) | Fixed export shares (5) | Fixed bilateral import shares (6) |
|---|---|---|---|---|---|---|
| Welfare change | | | | | | |
| Asia | −0.79 | −1.48 | −1.73 | −1.94 | −1.90 | −2.12 |
| Commonwealth of Independent States | −0.42 | −0.56 | −0.70 | −1.00 | −0.81 | −1.28 |
| Europe | −0.57 | −0.70 | −0.80 | −0.93 | −0.85 | −1.12 |
| Latin America | 0.18 | 0.07 | 0.15 | 0.30 | 0.24 | 0.63 |
| Middle East and North Africa | −1.41 | −2.14 | −2.40 | −2.65 | −2.85 | −2.88 |
| Northern America | −0.11 | −0.12 | −0.15 | −0.20 | −0.13 | −0.25 |
| Oceania | 0.17 | 0.24 | 0.23 | 0.19 | 0.28 | 0.23 |
| Sub-Saharan Africa | 0.12 | −4.82 | −6.55 | −8.14 | −7.21 | −10.11 |
| World | −0.47 | −0.85 | −1.00 | −1.15 | −1.09 | −1.30 |
| Agricultural good consumption | −12.11 | −18.23 | −20.22 | −21.87 | −21.65 | −23.57 |
| Agricultural good price | 30.64 | 56.38 | 66.83 | 79.38 | 76.40 | 94.89 |
| MAD of acreage shares | 72.35 | 65.02 | 64.12 | 63.47 | 64.94 | 63.29 |
| MAD of between-country acreage shares | 54.19 | 40.80 | 38.91 | 37.26 | 38.46 | 36.00 |
| MAD of international trade volumes | | 83.63 | 70.31 | 58.24 | 57.63 | 42.94 |

We would like now to compare the two counterfactuals with restrictions on trade. In all model variations, the counterfactual exercise where export shares are fixed using trade taxes leads to more moderate welfare losses than the restriction that fixes the bilateral import shares. In the case of the benchmark calibration, we can compare the restrictions' effects in columns 5 and 6 of table 7. Since both counterfactuals restrict trade adjustments, countries are obliged to rely more on their baseline trade patterns, so they experience much larger price increases than in the benchmark and larger decreases in the consumption of the agricultural good bundle, with a smaller effect for fixed export shares. However, in contrast with the counterfactual on acreage that blocks all acreage changes, the counterfactuals on trade do not block all trade adjustments. We measure how much they restrict trade changes through the MAD of international trade volumes.

The MAD of international trade volumes is 70% in the benchmark simulation. It decreases to 58% if export shares are fixed and 43% if bilateral import shares are fixed. We draw two conclusions from this observation. Firstly, fixing bilateral import shares maintains trade flows closer to their initial values than fixing export shares, indicating that the trade adjustments are more important on bilateral import shares than on export shares. Secondly, despite the strong restrictions imposed on trade by fixing bilateral import shares, the MAD of international trade volumes are large at 43%, showing that a lot of trade adjustments still take place. So, there may be other margins through which trade adjusts following climate change that could be interesting to study.

## 5.4 Costinot et al. (2016) calibration

CDS conduct an analysis similar to the one conducted in this paper. Their main results are available in the last row of table 6: they find a very important adaptive role for acreage adjustments and a negligible role for export shares adjustments. To help understand the differences between CDS' results and ours, we have also simulated our model using their behavioral assumptions, mostly combining parameter values previously tested. However, the two models are not nested, which makes the comparison necessary incomplete. Aside from the differences in behavioral parameters, the main differences are as follows. First, there is a difference in coverage. CDS' model covers the 10 most important crops and the 50 most important countries, while our model covers all GAEZ crops and all countries. Our larger crop coverage increases the size of the climate change shock and limits the role of acreage changes by ensuring that all the land in the model has a valuable use under current climate conditions. Second, livestock is absent from CDS, but once the elasticity of substitution between crops for feed is equalized with the elasticity of substitution between crops for food to CDS' value, this difference should have a limited effect. Finally, the modelings of crop production are slightly different, implying that the climate change shock is a total factor productivity shock in CDS and a land productivity shock in this paper and that there is an extensive margin over unused land in CDS.

To adjust the model's demand side to CDS' behavioral assumptions, it suffices to assume higher elasticities: a unitary demand elasticity for the food bundle and a substitution elasticity equal to 2.82 for final demand and demand for feed. Regarding the supply-side, and so the degree of within-field heterogeneity, $\theta$, even if this parameter has the same interpretation in their model and ours, it does not have the same quantitative effect. To make the two models comparable, we select $\theta$ to target their aggregate supply elasticity. From equation (8) in CDS, their supply elasticities can be derived:

$$\frac{\partial \ln Q_i^k}{\partial \ln p_i^k} = (\theta - 1) \sum_{f \in \mathcal{F}_i} \left(1 - \pi_i^{fk}\right) \frac{Q_i^{fk}}{Q_i^k} = (\theta - 1) \sum_{f \in \mathcal{F}_i} \left( \underbrace{1 - \sum_k \pi_i^{fk}}_{\text{Extensive}} + \underbrace{\sum_k \pi_i^{fk} - \pi_i^{fk}}_{\text{Intensive}} \right) \frac{Q_i^{fk}}{Q_i^k}. \tag{64}$$

This expression differs from equation (26) by the ratio of the producer price to the land rents, $p_i^k / r_i^k$, because our model allocates land according to the land rents, not according to the producer price. From their programs, we can calculate an average world acreage elasticity, weighted by the value of production, equal to 1.39. To reproduce the same average elasticity for the same set of crops in our model requires $\theta = 1.2407$, well below their value of 2.46, in part because of the role of $p_i^k / r_i^k$. Since supply elasticities are proportional to $\theta - 1$, increasing $\theta$ from 1.1 to 1.2407 amounts to more than double the elasticities from our benchmark. Models 18–22 of table 6 present calibrations using combinations of CDS behavioral assumptions.

When comparing results with CDS, there are one common result and two differences to comment. What is common is CDS' result that export share adjustments have a very small role in adaptation to climate change. Despite some variations, this result holds in table 6 independently of the chosen calibration. However, we have shown before that trade adjusts along other margins, leading to a non-negligible role in adaptation.

The first difference with CDS' results is relative to the order of magnitude of the welfare changes. Assuming an elasticity of substitution of 2.82 for final demand and demand for feed in model 18 is enough to bring down the welfare losses to the order of magnitude in CDS. Adding the assumption of a unitary elasticity for the final demand (model 19) brings the welfare results closer to CDS' but has a more limited effect.[11] With higher demand elasticities, adjustments occur more through quantities than through prices, and climate change is much less costly, since food consumption can be reduced at a limited welfare cost.

The second difference concerns the role of acreage adjustments, which is much more important in CDS than in this paper. In CDS, acreage adjustments reduce global welfare losses by 67%, while in the model with the closest calibration to CDS (model 22), they reduce losses by 46%. Calibrating the supply-side behavior to follow CDS' model (model 20) increases the role of acreage adjustments compared to our benchmark calibration from reducing losses by 37% to reducing losses by 46%, but it is still far from CDS' results, and increasing $\theta$ further does not further increase the role of acreage in this model (results not represented here). One difference between the two models could explain this discrepancy in the role of production adjustments: the extensive margin over "unused" land in CDS' model. We cannot prove it, since our model cannot account for this margin, but we can provide the following intuition. CDS supply elasticity can be decomposed as in equation (64) between an extensive margin (the contribution to the elasticity of the extension over "unused" land) and an intensive margin (the substitution between crops for a given area of agricultural land). If we consider the same set of crops, our model also includes an extensive margin over the other crops, in particular grass. A key difference is that this extension has an opportunity cost in our case because the land has an alternative valuable use. In CDS, the "unused" land on which crops can expand has no opportunity cost.[12] So, there is a factor supply of land only restricted by the availability of land and the labor cost to put land into production. Decomposing the supply elasticities shows that the extensive margin is the principal component, while the intensive margin is very small and negligible in some countries (see table **??** for an illustration). ~~These elasticities stand in contrast with most estimates in the literature , which instead show~~ The empirical literature does not provide evidence about the respective roles of the intensive and extensive margins over the very long run considered here, but most estimates available for a shorter horizon show instead that acreages adjust primarily on the intensive margin (see Kim and Moschini, 2018, for an illustration with maize and soybean in the U.S.).

From this perspective, these two different results, in CDS and in this paper, can be seen as two bounds for the contribution of acreage adjustments to adaptation to climate change. By assuming an extensive margin of land only restricted by land availability and labor cost, they provide an upper bound to the contribution of acreage adjustments. On the contrary, by neglecting the possibility to extend agricultural land, this paper provides a lower bound to the contribution of acreage adjustments.

# 6 Conclusion

This paper estimates how climate change in the agricultural sector will affect the world economy, focusing on the role of production and trade adjustments as margins of adaptation. Using an Armington quantitative trade model with spatially explicit land uses that builds on Costinot et al. (2016), we simulate a counterfactual scenario of climate change where

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[11] The fact that despite, different crop coverages, both models can reach similar welfare is a coincidence that can be explained by two elements. On the one hand, in GTAP data, land accounts for one-fifth of production costs on average and since our climate change shock is a shock to yield, this assumption reduces the size of the shock by ~~one-fifth~~ four-fifth compared to CDS where the shock applies to total factor productivity. On the other hand, we include many more crops in the model than they do. The subset of CDS' crops represents just 38% of the production value of all our crops. After combining these two differences, we should expect a lower climate change shock in our model, which could explain why welfare losses under full adjustments are lower when we adopt their behavioral assumptions (models 21 and 22) than in their benchmark (−0.26).

[12] There is no opportunity cost of land, but the labor required to work the land explains why some land is left unused.

the shock on crop yields at the 2080 horizon is based on simulations from crop science. In our benchmark calibration, climate change reduces welfare globally by 1%, with a lot of heterogeneity as net-food-importing tropical countries lose from the negative productivity shocks and increased global food prices, while countries exporting agricultural products tend to gain thanks to improved terms of trade.

These welfare changes are the results of demand-side, supply-side, and trade adjustments that all contribute to mitigate the adverse shock. Supply-side adjustments are crucial, allowing production to relocate where it is more profitable. The most important supply-side adaptation appears to be the ability to introduce crops that were not productive before climate change to a field, a feature made possible by the functional forms used in our spatially explicit modeling. Since these adjustments reallocate crop production between countries, as well as within countries, international trade plays a strong role in balancing the new domestic supply and demand schedules. If some trade adjustments are prevented from occurring by forcing bilateral import shares to stay constant, welfare losses increase by 30%. This result is in contrast with Costinot et al.'s (2016) result that only production adjustments matter in adaptation to climate change while trade adjustments would barely reduce welfare losses. This difference is explained by Costinot et al.'s different counterfactual for measuring the role of trade adjustments. They constrained export shares under climate change to the level of shares under current climate conditions. Under this counterfactual, welfare losses barely increase, showing the limited role of this adjustment margin, a result we confirm in this paper under a variety of calibrations. However, trade also adjusts along different margins, and given the heterogeneity of climate change impact across countries, we show that the ability to adjust import sources plays an important role in adaptation to climate change.

Adaptation to climate change in agriculture is often synonymous with investments in irrigation infrastructure, development of new crop varieties, or as confirmed by our paper, farm-level decisions regarding planting decisions and adjusting the crop mix to the new climate, which are indisputably important supply-side adjustments. But this paper demonstrates that these adjustments will not prevent the creation of large imbalances in domestic markets, which can only be resolved by large reallocations in international trade. While theses market adaptations depend naturally on the behavior of private agents in a competitive market and thus seem much less prone to the coordination failure we are witnessing on greenhouse gas emissions mitigation, they nevertheless rely significantly on an international trade system allowing very large reallocations of trade flows. Large terms-of-trade effects as predicted by our results may prompt uncooperative trade policies from policy makers to counteract these reallocations. If policies prevent trade adjustments as an avenue for adaptation, welfare losses would likely be worse in the long run. In this context, some of the difficulties related to international coordination that we face for mitigation may also plague adaptation. A rule-based trading system will be needed to enable climate change adaptation, so strengthening the role of the WTO should be viewed as integral to actively pursuing the agenda of the United Nations Framework Convention on Climate Change.

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