The Biophysical and Economic Geographies of Global Climate Impacts on Agriculture

Uris Baldos[1,2], Thomas Hertel[1,2,3,*] and Frances C. Moore[4],

1: Department of Agricultural Economics
Purdue University
403 West State St
West Lafayette, IN 47907

2: Global Trade Analysis Project
Purdue University
403 West State St
West Lafayette, IN 47907

3: Purdue Climate Change Research Center
203 S. Martin Jischke Drive
Gerald D. and Edna E. Mann Hall, Suite 105
West Lafayette, IN 47907

4: Department of Environmental Science and Policy
2140 Wickson Hall
University of California Davis
One Shields Ave
Davis, CA 95616

* Corresponding Author: hertel@purdue.edu

Abstract

This paper explores the interplay between the biophysical and economic geographies of climate change impacts on agriculture. It does so by bridging the extensive literature on climate impacts on yields and physical productivity in global crop production, with the literature on the economic geography of climate change impacts. Unlike previous work in this area, instead of using a specific crop model or set of models, we instead employ a statistical meta-analysis which encompasses all studies available to the IPCC-AR5 report. This comprehensive approach to the assessment of the biophysical impacts of climate change has the added advantage of permitting us to isolate specific elements of the biophysical geography of climate impacts, such as the role of initial temperature, and differential patterns of warming across the globe. We combine these climate impact estimates with the GTAP model of global trade in order to estimate the national welfare changes which are decomposed into three components: the direct (biophysical impact) contribution to welfare, the terms of trade effect, and the allocative efficiency effect. We find that the terms of trade interact in a significant way with the biophysical geography of climate impacts. Specifically, when we remove the biophysical geography, the terms of trade impacts are greatly diminished. And when we allow the biophysical impacts to vary across the empirically-estimated uncertainty range, taken from the meta-analysis, we find that the welfare consequences are highly asymmetric, with much larger losses at the low end of the yield distribution than gains at the high end. Furthermore, by drawing on the estimated statistical distribution of trade elasticities, we are also able to explore the *interplay between* economic and biophysical uncertainties. Here, we find that regional welfare is most sensitive to extremely adverse yield outcomes in the presence of uncertainty in trade elasticities.

1. Motivation and Literature Review

There is now a large literature documenting the effects of climate change on crop productivity. Scientific approaches to estimating the response of crops to changes in temperature, rainfall, and CO_2 concentration range from process-based crop models that simulate the biophysical processes occurring in plants, to reduced-form empirical approaches, to agronomic in-field or greenhouse experiments, but give quantitatively and qualitatively similar estimates of the effect of climate change (Liu et al., 2016; Lobell & Asseng, 2017; Zhao et al., 2017). While historically a large fraction of studies examined the impacts on a particular crop in a single area, recent efforts have attempted to consistently estimate impacts to multiple crops around the globe (Lobell, Schlenker, & Costa-Roberts, 2011; Moore, Baldos, Hertel, & Diaz, 2017; Rosenzweig et al., 2014). These studies tend to show a consistent picture of the 'biophysical' geography of climate impacts on agricultural productivity. For example, the effects are worse for cold-adapted wheat relative to heat-tolerant rice and effects are worse in hotter areas than cooler ones (Porter et al., 2014). The Agricultural Modeling and Intercomparison Project (AgMIP) has organized this community and they have made considerable progress over the past decade in characterizing the uncertainty associated with the biophysical impacts of climate change.

Although the yield impacts of climate change have been well-studied, the implications of these impacts for economic outcomes such as welfare, production, consumption, international trade, prices and welfare has received less attention, despite the fact that these outcomes are of more direct interest for both adaptation and mitigation policies. (See Reilly and Hohmann (1994) and Rosenzweig and Parry (1994) for some notable exceptions.) Examining only the effects of local productivity changes could be extremely misleading since climate change is expected to have global impacts and since many agricultural products are heavily traded internationally. Recently an increasing number of papers have used the biophysical yield results described above as an input to general- or partial-equilibrium models in order to model the economic consequences of productivity shocks. Nelson and Shively (2014) provide an overview of a special issue of the journal *Agricultural Economics* in which ten global economic models (loosely termed the AgMIP economic modeling group) are linked to the AgMIP archives of biophysical impacts in order to draw out the implications for the future agricultural economy of climate change in the context of five different 'Shared Socioeconomic Pathways'. These models include both partial and general equilibrium approaches, and the focus is on comparing model results for regional and global prices, production, consumption and land use change. Relatively little attention is devoted to trade – indeed the models in this group have very different treatments of international trade – nor do they explore the potential role for trade to facilitate adaptation to climate change.

In a subsequent paper, also drawing on the AgMIP archive of biophysical climate impacts on crop yields, Baldos and Hertel (2015) focus explicitly on the role of trade in mitigating the impacts of climate change on undernutrition. Their partial equilibrium model predicts a dramatic increase in undernutrition in South Asia under a *worst-case* climate impacts scenario from the AgMIP archives, but they also find that fully integrating global crop commodity markets could cut this increase in half, by giving consumers in the hardest hit regions better access to world markets. However, these authors do not explore the geography of trade – indeed, in the case of fully integrated markets, they apply the law of one price which effectively eliminates this geography.

A somewhat separate strand of literature has used simpler, empirically-estimated trade models that emphasize the importance of geography in determining trade costs and therefore the welfare-gains from trade. The most notable paper in this tradition is that of Costinot, Donaldson and Smith (2016). Those authors emphasize the importance of the spatial dispersion of yield changes or, in the vocabulary of the present paper, the *biophysical geography* of climate impacts on agriculture.

Costinot, Donaldson and Smith (2016) note that this opens possibilities for additional gains from trade by which “a country may stop producing a crop whose yields have fallen and import it in exchange for another crop whose yields have remained constant at home.” Their paper focuses on climate-induced changes in comparative advantage, both within and across countries. The most salient finding from their paper is that the domestic adjustments in production location are more important than international trade in mitigating potential losses from climate change.

A significant limitation of Costinot, Donaldson and Smith (2016) is their reliance on a single model, the FAO GAEZ model, to elicit yield impacts of climate change across the world. The GAEZ model reports potential yields (i.e. yields without any nutrient or moisture constraints), rather than actual yields (Rosenzweig et al. 2014). For this reason it is difficult to validate model output (since potential yields are not observed) and also is likely to result in biased estimates of the productivity impacts of climate change because of the interaction between nutrient and moisture availability and the effect of CO_2 fertilization, precipitation change, and temperature change.

Our paper seeks to begin the process of bridging these different literatures, focusing specifically on the interplay between the biophysical and economic geographies of climate impacts on agriculture, international trade and economic welfare. In doing so we seek to combine some of the strongest elements of both literatures: productivity shocks are based on a meta-analysis of the current yield impacts literature that was used to support findings in the recent IPCC assessment report (IPCC, 2014), combined with an empirically-based trade model with clear welfare-theoretic foundations which allows us to decompose the welfare consequences of climate change on agriculture into constituent drivers.

As noted by Costinot, Donaldson and Smith (2016), if all crops, in all regions, were affected in the same way by global warming, this would be a relatively simple problem – and there would be a very limited role for international trade in adapting to climate impacts. Indeed, from a welfare-theoretic point of view, a ‘first cut’ estimate of the (e.g.) welfare loss from lower yields would be based on the valuation of lost output at market prices. To this, we would need to factor in the impact of changing prices on regional welfare. Here, one would simply need to know if a given region was a net seller or net buyer of crops in order to deduce whether a given region would gain or lose from the terms of trade effects of climate change. However, the world is not that simple. Climate impacts on crops vary, for example, due to differences in the pattern of global warming across the world, as well as differences in initial temperatures. The impacts of elevated temperatures and higher CO2 concentrations vary by crop, and crop composition varies widely across the globe. It is for these reasons that the inter-regional incidence of climate change becomes an interesting problem, worthy of deeper investigation.

Our first task in this paper will be to understand the biophysical geography of climate-induced agricultural impacts. We will do so using a newly available meta-analysis of more than 1,000 climate impact estimates submitted as part of the IPCC AR5 review process (Moore, Baldos, & Hertel, 2017; F. C. Moore et al., 2017). With this meta-function in hand, we can isolate the impact of different drivers of differences in the biophysical geography of impacts. We start by examining the full climate impacts, then decompose the contributions of: (a) differences in temperature increases across the globe (pattern scaling), (b) differences in initial temperature (warm vs. cold regions), and (c) differences in crop composition. This contributes to an improved understanding of the biophysical geography of climate impacts – a necessary precursor to analyzing the economic geography of the interregional incidence.

In order to assess the inter-regional incidence of climate change, we need to introduce a global economic model. Here, we adopt a quantitative, global general equilibrium approach to this problem in order to ensure complete measurement of the welfare effects. Even though agriculture comprises a relatively small share of industrial economies, it remains a critical source of employment in the world's poorest economies – many of which are also highly vulnerable to climate change. Furthermore, agriculture is closely linked to the rest of the economy -- backwards through input markets and forwards through food processing. When combined, these sectors represent a significant share of GDP many countries. In addition, the terms of trade effects from global climate change impacts on these widely traded commodities are ultimately spread across all merchandise goods and services in the process of achieving balance of payments equilibrium. Therefore, a general equilibrium approach is appropriate.

In order to avoid the 'black-box' critique often leveled at applied general equilibrium models, we systematically decompose the sources of all regional welfare changes. There are three components of welfare change in our model: the direct productivity effect (essentially just the local productivity change multiplied by crop value), the terms-of-trade effect, and the allocative efficiency effect (caused by interactions with existing market distortions). While the efficiency effect is found to be relatively modest in most regions, the terms-of-trade (ToT) effect can be quite important. In a number of cases the ToT effect reverses the sign of the welfare change from the productivity effect. In other words, a number of regions experience, for instance,yield losses but welfare gains because the increasing value of exports more than compensates for the productivity losses. This prompts us to delve more deeply into the terms of trade impacts from climate change and their interplay with the underlying biophysical geography of climate impacts.

A natural way to explore the interplay between the biophysical and economic geographies of climate change is to gradually introduce sources of biophysical variation and, at each stage, re-evaluate the terms of trade effects. Our meta-analysis permits this decomposition, and reveals biophysical heterogeneity reinforces the importance of economic geography, with the size of the terms of trade effects growing as we introduce varying climate impacts based on crop composition, initial temperature and pattern-scaling of temperature changes due to global warming.

Of course, the importance of ToT effects depends on the magnitude of relative price changes, which, in turn, depend on the productivity shocks. If the effect of climate change is primarily to redistribute production around the globe rather than to increase or decrease aggregate production, then ToT effects will be smaller. This interplay takes us into the realm of uncertainties associated with both the biophysical impacts of climate change and the economic responses to these shocks, as well as their interactions. In order to understand the role of these uncertainties, we return to the underlying statistical models used to estimate the climate impacts as well as the responsiveness of international trade flows and extract confidence intervals for the underlying economic parameters. This provides the foundation for an experimental design aimed at understanding these interactions.

2. Theory

Since our focus in this paper is on regional welfare changes, we begin with the analytical expression (1) for the change in welfare (measured as Equivalent Variation or EV) due to climate change shocks to agricultural productivity, θ_{is} , which represent the % change in Hicks-neutral productivity of sector *i* of region *s.* (See Huff and Hertel (2001) for a complete derivation of this expression.) It is quite intuitive that, if farmers plant the same crop using the same mix of inputs at mid-century, but harvest 10% less output, then the direct economic loss is simply equal to 10% of the value of output ($PO_{is}QO_{is}$). This is summed across all sectors in region *s* to obtain the *direct welfare effect of climate change*. (Note, however, that we will only be perturbing θ_{is} for a subset of sectors in the analysis below.)

$$EV_s = (\psi_s)\left\{\begin{array}{l} \sum_{i=1}^{N} (\theta_{is} PO_{is} QO_{is}) \\ + \sum_{i=1}^{N} \sum_{r=1}^{R} (\tau_{Mirs} PCIF_{irs} dQMS_{irs}) \\ + \sum_{i=1}^{N} (\tau_{Ois} PO_{is} dQO_{is}) \\ + \sum_{i=1}^{N} \sum_{r=1}^{R} (QMS_{irs} dPFOB_{irs}) \\ - \sum_{i=1}^{N} \sum_{r=1}^{R} (QMS_{irs} dPCIF_{irs}) \end{array}\right\} \quad (1)$$

The next two terms in this welfare decomposition capture how these perturbations, when implemented globally, interact with existing policy distortions, thereby accounting for *changes in allocative efficiency* due to the climate shocks.[1] Consider what happens when the production of a staple commodity *i* in region *s* is disproportionately adversely affected by climate change. Assuming consumers seek to maintain consumption of this staple good, the country will need to import more of the product. If production of this staple commodity has been protected by domestic agricultural policies, then there is likely to be a tariff on its importation ($\tau_{Mirs} > 0$), as well as a subsidy on its production ($\tau_{Ois} > 0$). *Ceteris paribus*, importing more of this staple commodity ($dQMS_{irs} > 0$) and producing less of it ($dQO_{is} < 0$) will improve allocative efficiency and thereby raise regional welfare, as they access more of the product from lower cost suppliers overseas. Of course, the opposite outcome is also possible – and indeed quite likely -- since wealthier countries in the Northern latitudes tend to protect agriculture as well as potentially standing to benefit from higher temperatures in the wake of longer growing seasons for their crops.

The final two terms in equation (1) refer to *the terms of trade (ToT) effects* for region *s*, due to the climate change shocks. The ToT effects sum to zero globally and so are pure transfers at that

[1] In equation (1) we show only tariffs and output subsidies, which are the predominant types of distortions in agricultural markets. However, in the computational general equilibrium model, we must consider all distortions in all sectors of the economy, so this expression has many additional terms.

level. This offers an avenue for a region heavily affected by climate change, which is also a major commodity exporter, to share the burden of climate change with other regions. If region *s*'s production is disproportionately hit by higher temperatures, its export-weighted FOB prices are likely to rise, relative to her import-weighted CIF prices. In this case, her TOT will improve, while those of her trading partners (importers) are likely to deteriorate. In summary, each region's welfare gains can be decomposed into three components: direct effects of climate change, allocative efficiency effects and the terms of trade component. This decomposition will prove very useful when it comes to understanding the interregional incidence of climate change impacts on agriculture.

At this point, the astute reader will note that expression (1) is only locally valid. In order to operationalize this decomposition tool in a quantitative general equilibrium model, such as that discussed below, this welfare decomposition must be numerically integrated, allowing the prices and quantities to change over the course of the model solution. We use version 8 of the GEMPACK software suite (Harrison and Pearson, 2002) which is ideally suited to this problem, as it solves the non-linear CGE model using a linearized version of the behavioral equations, coupled with updating equations that link the change in imports, $dQMS_{irs}$, for example, with the levels variables, QMS_{irs}, thereby integrating the terms in this decomposition over large changes in the underlying variables. Standard extrapolation techniques can be used to obtain arbitrarily accurate solutions this well-posed non-linear problem (W. J. Harrison & Pearson, 1996).[2]

[2] For purposes of this paper, we require that 95% of the variables and levels variables are accurate to six digits. Another useful check is to compare EVs computed from equation (7) with that computed directly from the utility function. These match, to machine accuracy.

3. Estimating climate impacts on agriculture

In order to operationalize this theory, our first task is to estimate the shocks to agricultural productivity, by commodity and region: θ_{is} . We do so by drawing on the recent meta-analysis of Moore et al. (2017a, 2017b). The yield-temperature response functions used in this paper are derived from a database of studies estimating the climate change impact on yield compiled for the IPCC 5th Assessment Report (Porter et al., 2014), also described in a meta-analysis by Challinor et al. (2014). For the four crops addressed here, the database contains 1010 observations (344, 238, 336, and 92, for maize, rice, wheat and soybeans respectively) from 56 different studies published between 1997 and 2012. The database underlying our yield shock estimates is therefore based on a comprehensive review of the current agronomic literature that supported conclusions in the food security chapter of the most recent IPCC report.

We merge this database with information on baseline growing season temperature for each data-point using planting and harvest dates from Sacks et al. (2010) and gridded monthly temperatures for 1979-2013 from the Climate Research Unit (CRU, 2016). These were averaged to the country level using year 2000 crop production weights from Monfreda et al.(2008). This allows us to estimate the response of all four crops using the following:

$$\Delta Y_{ijk} = \beta_{1j}\Delta T_{ijk} * Crop_j + \beta_{2j}\Delta T_{ijk}{}^2 * Crop_j + \beta_{3j}\Delta T_{ijk} * Crop_j * \bar{T}_{jk} + \beta_{4j}\Delta T_{ijk}{}^2 * Crop_j * \bar{T}_{jk} + \beta_5 f_1(\Delta CO_{2ijk}) * C_3 + \beta_6 f_2(\Delta CO_{2ijk}) * C_4 + \beta_7\Delta P_{ijk} + \beta_8\Delta T_{ijk} * Adapt_{ijk} + \beta_9 Adapt_{ijk} + \varepsilon_{ijk} \quad (2)$$

Where ΔY_{ijk} is the change in yield from point-estimate i for crop j in country k (in %). $\Delta T_{ijk}, \Delta CO_{2ijk}$ and ΔP_{ijk} are the changes in temperature (in degrees C), CO_2 concentration (in parts per million (ppm)) and rainfall (in percent) for point-estimate ijk, $\bar{T}_{jk}$ is the baseline growing-season temperature for crop j in country k, C_3 and C_4 are dummy variables indicating whether the crop is

C_3 or C_4, and $Adapt_{ijk}$ is a dummy variable indicating whether the point-estimate includes any on-farm adaptation. Equation 1 is estimated using an ordinary least squares regression. Uncertainty in the parameters is estimated through 1500 block bootstraps, with blocks defined at the study level, allowing for possible correlation between point-estimates from the same study.

Equation (2) allows for a non-linear, crop-specific warming response that is allowed to differ between hot and cold locations. It includes a diminishing marginal effect of CO_2 fertilization, allowed to differ between C_3 and C_4 crops. (Specifically, the function takes the form $f(\Delta CO_{2ij}) = \frac{\Delta CO_{2ij}}{\Delta CO_{2ij}+A}$ where A is a free parameter set at 100ppm for C_3 crops and at 50ppm for C_4 crops based on a comparison of the R^2 across models using multiple possible values.) Finally, it allows the effect of warming to vary depending on whether the study reports including adaptation, but we find the adaptation effect to be small.

In addition to Equation (2), our preferred specification, we investigate the effects of several alternate specifications. Specifically we: 1) investigate whether newer studies (publication date of 2005 or later) give a different temperature response compared to the full sample; 2) investigate the effect of individual agronomic adaptations, specifically changing cultivar and planting date; and 3) allow the effect of temperature to differ depending on whether the study was a process-based or empirical study. These robustness checks are documented in Moore et al. (2017b) and do not significantly alter the estimated crop response to temperature. We also investigate block bootstrapping at the model rather than the study level and do not find this substantially increases our standard errors. The latter will be used to characterize uncertainty in climate impacts.

Using the response function estimated in Equation (2), we predict yield shocks on a global 0.5° grid for 2°C of global average warming. Local temperature change at 2°C warming is calculated based on the pattern scaling of the CMIP5 multi-model ensemble for RCP8.5 (Taylor, Stouffer, & Meehl, 2007). (See appendix Figure A1 for a map of these scaling factors.) All yield shocks in this paper also include the estimated benefits of CO_2 fertilization and the benefits of on-farm agronomic adaptations. Figure 1 shows these gridded yield shocks at 2 degrees of warming. Consistent with the large literature on temperature productivity effects on agriculture, we find negative impacts over much of the world that are only partially offset by the benefits of CO_2 fertilization. There are some positive effects particularly for rice and soybeans at higher latitudes. Negative impacts are larger in continental interiors (where local warming is larger) and in hot places (where sensitivity to warming is higher).

For a particular crop, the biophysical pattern of climate change for crop yield at 2°C warming varies depending on 1) initial growing season temperature and 2) the magnitude of local warming based on the pattern-scaling between local and global temperature change. In order to isolate the effect of these drivers of the geographic pattern of yield shocks we first standardize the temperature shock by replacing the temperature change in each location with the area-weighted average temperature change for each crop. This removes the pattern-scaling. By deducting the direct effects of climate change on economic welfare under this restricted scenario, with that obtained under the unrestricted experiment, we can obtain the direct welfare impacts of pattern-scaling. Secondly we remove the geographic pattern associated with varying sensitivity to warming by standardizing initial growing-season temperatures at the area-weighted global average value for each crop. Deducting the resulting welfare change from the previous (no pattern scaling) welfare, we obtain the effect of initial temperature on direct welfare impacts. In a final experiment, in addition to removing pattern scaling and setting initial temperatures equal, we equate individual crop responses (same coefficients for all crops, j, in equation (2))in order to remove the final element of biophysical geography. Deducting welfare by region from the prior result gives us the impact of crop composition on the direct welfare effects of climate change by country.

4. The quantitative trade model

One of the most widely used quantitative general equilibrium models is the Global Trade Analysis Project model (Hertel, 1997). Use of this model has the advantage that it is open-source, is used by thousands of individuals around the world, and has been successively refined over the course of the last two decades.[3] The version used here assumes perfect competition and constant returns to scale which are generally deemed to be reasonable assumptions for sector level modeling of agriculture in the presence of free entry and exit (Diewert, 1981). Products are assumed to be nationally differentiated, but homogeneous within each country. The product differentiation is by origin using the method of Armington (1969), which, once again, is generally deemed appropriate for agricultural products – particularly the field crops which are the focal point of this paper.

The GTAP model runs on any desired aggregation of the GTAP data base, which now in its 9th release (Aguiar, Narayanan, & McDougall, 2016)[4] and which contains the most comprehensive set of fully integrated, globally exhaustive, information on agricultural production, consumption, trade, tariffs and domestic agricultural policies. Version 9.1 of the data base, which is used here, disaggregates the global economy into 140 regions – of which 120 are individual countries for which primary data have been assembled, reconciled and integrated into the overall data base. Tariff data come from the International Trade Centre in Geneva, which is responsible for collecting tariff data for the United Nations, while the domestic agricultural support measures are obtained from the OECD and the European Commission (Aguiar et al., 2016). Reconciled bilateral merchandise trade data come are obtained using the methodology outlined in Gehlhar (1996).

[3] Refinements and extensions of the standard model are available here: (https://www.gtap.agecon.purdue.edu/resources/tech_papers.asp)
[4] Documentation and downloads of the data is available here: (https://www.gtap.agecon.purdue.edu/databases/v9/default.asp),

As we will see in the results section, parameterization of the model – particularly the trade elasticities -- is critical to our results. Here, we draw on the work of Hertel, Hummels, Ivanic and Keeney (2007) which estimates the equation (3) using 5-digit, SITC customs data compiled by Hummels (1999, p. 199) for six importers in the Americas and New Zealand giving rise to 187,000 observations on both *fob* and *cif* values:

$$\ln V_{irs} = a_0 + a_{is} + a_{ir} + \beta_{0,i} \ln(1+ freight_{irs} + tariff_{irs}) + \beta_{1,i} \ln Dist_{rs} + \beta_{2,i} Lang_{rs} + \beta_{3,i} Adj_{rs} + \varepsilon_{irs} \qquad (3)$$

where V_{irs} is bilateral trade for commodity *i* from *r* to *s*, in value terms, a_{is} and a_{ir} are vectors of importer-commodity and exporter-commodity intercepts, $freight_{irs}$ and $tariff_{irs}$ are the *ad valorem* rates for international shipping/insurance and tariffs of commodity *i* moving from *r* to *s*, Dist measure distance on that route, similarity of language is denoted *Lang*, and adjacency of the trading countries is given by the indicator variable *Adj*. The parameter of interest in this study is $\beta_{0,i} = 1 - \sigma_i$, which is identified from bilateral variation in trade costs. The model is estimated specifically for use with the GTAP model, so that the OLS estimates of $\beta_{0,i}$ are constrained to be equal for all 5-digit categories within a given GTAP merchandise sector (of which there are 40). Estimates for the crops sectors of interest in this study (see Table A1) are all significant at the 95% confidence level and vary within the crops category from 2.6 for cereal grains *not elsewhere classified* (a very heterogeneous grouping) to 10.1 for paddy rice. Importantly for this paper, we obtain not only a point estimate, but also the standard error associated with each estimate. This will facilitate our subsequent analysis of the sensitivity of model results to parametric uncertainties.

5. Results

In this section, we build up the results in stages in order to better understand the biophysical and economic determinants of the interregional incidence of agricultural climate impacts.

Biophysical geography of climate impacts: We begin with the direct effect of climate change on regional welfare from equation (1): $EV_{direct,s} = (\psi_s)\left\{\sum_{i=1}^{N} (\theta_{is} PO_{is} QO_{is})\right\}$. As previously noted, this direct effect can be further decomposed using Equation 2, into three contributing factors, based on the underlying biophysical determinants of climate impacts. These include: differential rates of warming, differences in initial temperature, and differences in crop composition. Figure 2 reports these welfare changes from the direct productivity effect, in the form of global maps. For each region, the direct effect is normalized by the initial value of output for the four crops in question, i.e. $\left\{\sum_{i=1}^{4} (PO_{is} QO_{is})\right\}$ to correct for the fact that the relative importance of these crops varies greatly across the world. So the change in welfare is reported here as a percentage of the value of output under climate impact evaluation.

Panel A in Figure 2 reports the *total direct effect* on welfare of a two degree global mean temperature rise. The effects are mixed, with countries in the higher latitudes (and high altitudes – e.g., along the Andes) sometimes gaining more/losing less, and countries in the tropics and mid-latitudes hurt more. We can speculate about what is driving, for example, the large losses in Brazil, or the gains in China, but it is more useful to employ our meta-analysis function to decompose these losses. Panel B in Figure 2 reports the contribution of initial temperature to these direct welfare impacts. Here, we see that part of the reason for Brazil's losses is the high starting temperature in the grid cells where the four focus crops are grown. On the other hand, part of the reason for China's gains is the lower initial temperature in its cropping regions. Figure 2C reports the contribution of pattern-scaling to direct welfare impacts stemming from climate change. The northern latitudes are, incrementally, adversely affected by the polar amplification of global warming. After controlling for varying growing-season temperatures, Canada and Russia, for example, are disproportionately hurt by the uneven rate of global warming, whereas Brazil benefits from a more modest temperature rise due to pattern scaling.

The final panel (D) in Figure 2 shows the contribution of crop composition to the direct welfare effects. Recall from Figure 1 that the impact of 2 degrees C global warming on soybeans is much more severe than for rice. This means that, compared to the global average crop impact, soybeans in Brazil are hit much harder than rice in China. Given the predominance of these crops in those respective countries, crop composition favors China (blue coloring), while disadvantaging Brazil (red), as well as the other major soybean producers in Latin America.

With a sharp reduction in soybean output, relative to the no-climate change baseline, we expect that soybean prices will rise, thereby benefiting these exporting regions. How much of the pain of climate change can be shared with soybean importers? To answer this question, we must turn to the trade model and the economic geography of climate impacts.

Economic geography: We break the discussion of economic geography into two parts. We first analyze the terms of trade effect: $EV_s = (\psi_s)\left\{\begin{matrix} \sum_{i=1}^{N}\sum_{r=1}^{R}\left(QMS_{irs}dPFOB_{irs}\right) \\ -\sum_{i=1}^{N}\sum_{r=1}^{R}\left(QMS_{irs}dPCIF_{irs}\right) \end{matrix}\right\}$, which tells us how much of the (e.g.) loss from climate change can be shifted onto those countries buying the affected goods, in the form of higher prices. Conceptually, answer to this question comes in the form of a 140x140 matrix, describing the impact of a climate affected region (a row in the matrix) on every other region in the model (a column). (Note that, since the ToT effect will be spread across all sectors, it is important to evaluate this expression with respect to the full set of merchandise and services sectors in the model.) However, computing the elements of this matrix poses a challenge. One approach would be to shock each of the 140 countries, one-at-a-time and record the impacts on each of the 140 countries' terms of trade. However, this suffers from an important flaw – the climate shocks interact with one another and so the column totals will not reflect the ToT effect of the combined climate change experiment. Furthermore, the elements in the ToT matrix will no longer sum to zero, bringing the entire welfare calculation into question. Fortunately, Harrison et al. (2000) discovered a solution which has been implemented into the GEMPACK software used in this paper (J. Harrison, Horridge, and Pearson 2000; W. J. Harrison and Pearson 1996). Their subtotal function utilizes numerical integration techniques to partition the impacts of each individual shock on each variable in the model. So we are able to obtain a 140x140 matrix of ToT effects exchanged amongst regions in the wake this climate change experiment.

Figure 3A provides a partial visualization of this matrix. Across the top (Panel A) we see a 2 x 140 matrix, with the cells shaded to reflect gains (blue) and losses (red), evaluated as a percentage change in the country's overall ToT. The rows represent two of the world's largest crop exporters: Brazil and USA. Below Figure 3A appear two more figures (3B and 3C), which display the elements of the Brazil and US rows within a map of the world. Consider Figure 3B, which maps the elements of the Brazilian impact row of the ToT matrix. The adverse climate shocks in Brazil restrict Brazilian soybean output and raise world soybean prices, thereby benefitting Brazil (as well as her soybean producing neighbors). The biggest losses come in China and North Africa – both big importers of Brazilian crops. Note that the US, as a soybean competitor with Brazil, also gains from the Brazilian climate shocks. Figure 3C shows a similar map, only this time reporting the subtotals pertaining to the US climate shocks displayed in the USA row of Panel A. As competitors with the US, Canada, Brazil and Argentina gain, while those importing US agricultural products (Mexico and China, for example) lose. Similar maps can be constructed based on columns from the ToT matrix, in which case we can observe (e.g.) the way in which a given country is affected by climate change in all the countries of the world (see Appendix Figure A2 for an example).

The third, and final, element of the global geography of climate impacts is the allocative efficiency component of equation (1): $EV_s = (\psi_s)\left\{\begin{array}{l} +\sum_{i=1}^{N}\sum_{r=1}^{R}(\tau_{Mirs}PCIF_{irs}dQMS_{irs}) \\ +\sum_{i=1}^{N}(\tau_{Ois}PO_{is}dQO_{is}) \end{array}\right\}$. This is mapped, for the world, in panel C of Figure 4. It captures the interplay between existing distortions and changing trade and production flows in the economy. In fact, given the presence of taxes and subsidies on intermediate inputs and consumption in the GTAP data base, there are many more terms in the allocative efficiency effect captured in Figure 4C (beyond those shown in equation (1)). However, the predominant 'action' derives from changes in bilateral trade and output of agricultural products. A particularly interesting case is that of China, where soybean production is heavily subsidized. As climate change reduces soybean output in the US, Brazil and Argentina, world prices rise and China is encouraged to produce more soybeans. However, as their heavy subsidies suggest, this is not a commodity in which China has a comparative advantage. Therefore, this expansion of soybeans, and the accompanying reduction in imports, result in a loss of efficiency – hence the red shading for China in Figure 3C.

Interactions between Biophysical and Economic Geographies: How to these biophysical and economic features of the global geography of climate change interact? We investigate this question by simulating the global general equilibrium model once again, but this time without the biophysical differences noted previously. Figure 5 plots the terms of trade effects arising from this simulation (no biophysical geography = horizontal axis) against those arising from the full geography simulation (vertical axis) for the 140 regions in our model. From the slope of the underlying trend line, it is clear that the terms of trade impact is much more pronounced (more than double, on average) when the full biophysical geography is present. *The biophysical and economic impacts of climate change reinforce one another*.

Interactions between the Biophysical and Economic Uncertainties: Thus far we have been treating our estimates of climate impacts on crop yields, as well as trade elasticities, as certain, but both are highly uncertain. In this section of the paper, we explore the consequences of this uncertainty for the interregional incidence of climate change. For this, we run a series of eight additional experiments (the ninth, or central experiment, is already reported above). These are the elements of a 3 x 3 experimental design matrix in which the columns refer to climate impact uncertainties and the rows refer to economic response uncertainties. In both cases, we choose estimates from the 2.5, 50 and 97.5 percentiles of the distribution of estimated yield impacts and trade elasticities, respectively. This permits us to explore the interplay between the biophysical and economic uncertainties underlying this problem.

Figure 6 reports these welfare impacts (expressed as a percentage of initial expenditure on all goods and services – and therefore a small number since we are only considering impacts on 4 crops) for all 140 regions – arrayed in the following manner. The red, black and green lines show the welfare change for each region, evaluated at the low, median and high biophysical yield estimates based on the meta-analysis in equation (2). Through each of these point estimates runs an 'error bar' reporting the welfare change extending from the estimates with low and to high values drawn from the distribution of estimated trade elasticities. Several points are immediately evident. First of all, the mean impacts – that is the impacts evaluated at mean yield and mean trade elasticities – are mostly negative but are modest in size. Secondly, the welfare impacts of biophysical uncertainty are asymmetric. At high yields, the welfare deviations from the mean impacts are far smaller than the welfare changes induced by drawing from the low end of the climate-laden yield distribution. This is partly a result of asymmetric uncertainties in the yield response function (determined through a non-parametric estimation of the confidence intervals), but is exacerbated by the disproportionate welfare effects of very adverse productivity shocks. This underscores the downside risk associated with climate impacts being worse than expected. In this case, there could be substantial welfare losses to the most vulnerable economies. The asymmetric risk stemming from biophysical uncertainties is further compounded by the uncertainty in the trade elasticities. This too, has an asymmetric impact on welfare. With a few exceptions, the welfare impact of varying the trade elasticities is larger effects in the presence of low yield realizations.

In order to explore this interplay more fully we refer next to Figure 7 which organizes the same information in a different way. Each of the panels in this figure refers to a different draw from the biophysical impacts distribution. The first panel corresponds to the most adverse climate impacts (2.5 percentile), while the second and third refer to the modal (50^{th} percentile) and high (97.5 percentile) yield outcomes. Here, it is clear that the mean yield shocks have a limited impact on regional welfare and are therefore potentially of less interest. Also, it is hardly surprising that, when the climate outcome is more positive (97.5^{th} percentile), most regions tend to gain, while the low draw (2.5^{th} percentile) results in the majority of countries losing from the climate impacts on these 4 major crops.

The scatterplot in each the panels in Figure 7 plots the welfare change under the modal trade elasticity (50^{th} percentile), against that obtained from simulating the model with the low (2.5^{th} percentile = red diamonds), medium (black dots) and high (97.5^{th} percentile = black triangles) trade elasticities. By construction, the black dots lie along the 45 degree line. The interesting question is how much the diamonds and black triangles deviate from the 45 degree line. Generally speaking, the deviations are greatest for the red diamonds, suggesting that the welfare effects of climate changes are most pronounced when the trade elasticities in the model are at the lower end of the estimated distribution. This makes sense, since smaller trade elasticities require larger price changes in order to re-equilibrate markets in the wake of a climate change shock. A further observation is that this variation in the trade elasticities is most important (i.e., the divergence from the 45 degree line is largest) when the climate shock is adverse.

6. Conclusions

This paper contributes to the literature on the economic consequences of global climate change impacts on agriculture by exploring the interplay between the biophysical and economic geographies of the problem. It does so by bridging the extensive literature on climate impacts on yields and physical productivity in global crop production, with the less-well developed literature on the economic geography of climate change impacts. As with the Global Gridded Crop Model Intercomparison coordinated by AgMIP, as well as the work of Costinot, Donaldson and Smith (2016), we evaluate the impacts of climate change on a global grid. However, instead of using a specific crop model or set of models, we instead employ a statistical meta-analysis which encompasses all studies available to the IPCC-AR5. Not only is this approach more comprehensive, it also permits us to isolate specific elements of the biophysical geography of climate impacts, such as the role of initial temperature, and differential patterns of warming across the globe. This statistical meta-analysis also allows for a more sophisticated analysis of the uncertainties associated with climate impacts on agriculture in which we explore the consequences of outcomes at the tails of the climate-laden yield distribution.

In order to explore the welfare consequences and economic interplay with this biophysical geography, we use the GTAP model of global trade, coupled with econometrically estimated trade elasticities. This allows us to decompose the sources of welfare changes into three components: the direct (biophysical impact) contribution to welfare, the terms of trade effect and the efficiency effect. We find that the terms of trade interact in a significant way with the biophysical geography of climate impacts. When we remove the biophysical geography, the terms of trade impacts are greatly diminished. And when we allow the biophysical impacts to vary across the estimated distribution taken from the meta-analysis, we find that the welfare consequences are highly asymmetric, with much larger losses at the low end of the yield distribution than gains at the high end. Furthermore, by drawing on the estimated statistical distribution of trade elasticities, we are also able to explore the *interplay between* economic and biophysical uncertainties. Here, we find that regional welfare is most sensitive to low yield outcomes in the presence of low yield elasticities.

An important limitation of this work is the fact that we have modeled farmer responses to climate change (both the extensive and intensive margins) at the country level. Yet Costinot, Donaldson and Smith (2016) argue that the largest economic adjustments are likely to come from the reallocation of production within countries. Future work should combine the approach used here with a global, gridded economic modeling approach so that the economic consequences of the heterogeneous biophysical geography can play out at a sub-national level.

References

Aguiar, A., Narayanan, B., & McDougall, R. (2016). An Overview of the GTAP 9 Data Base. *Journal of Global Economic Analysis*, *1*(1), 181–208.

Armington, P. S. (1969). A Theory of Demand for Products Distinguished by Place of Production (Une théorie de la demande de produits différenciés d'après leur origine) (Una teoría de la demanda de productos distinguiéndolos según el lugar de producción). *Staff Papers (International Monetary Fund)*, *16*(1), 159–178. https://doi.org/10.2307/3866403

Baldos, U. L. C., & Hertel, T. W. (2015). The role of international trade in managing food security risks from climate change. *Food Security*, *7*(2), 275–290. https://doi.org/10.1007/s12571-015-0435-z

Challinor, A. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R., & Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change*, *4*(4), 287–291. https://doi.org/10.1038/nclimate2153

Costinot, A., Donaldson, D., & Smith, C. B. (2016). Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World. *Journal of Political Economy*, *124*(1), 205–248.

CRU. (2016). Temperature Data. Retrieved from https://crudata.uea.ac.uk/cru/data/temperature/

Diewert, W. E. (1981). The Comparative Statics of Industry Long-Run Equilibrium. *The Canadian Journal of Economics / Revue Canadienne d'Economique*, *14*(1), 78–92.

Gehlhar, M. (1996). *Reconciling Bilateral Trade Data for Use in GTAP* (GTAP Technical Paper No. 10). Department of Agricultural Economics, Purdue University, West Lafayette, IN: Global Trade Analysis Project (GTAP). Retrieved from https://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=313

Harrison, J., Horridge, M., & Pearson, K. (2000). *Decomposing Simulation Results with Respect to Exogenous Shocks*. Department of Agricultural Economics, Purdue University, West Lafayette, IN: Global Trade Analysis Project (GTAP).

Harrison, W. J., & Pearson, K. R. (1996). Computing solutions for large general equilibrium models using GEMPACK. *Computational Economics*, *9*(2), 83–127.

Hertel, T., Hummels, D., Ivanic, M., & Keeney, R. (2007). How confident can we be of CGE-based assessments of Free Trade Agreements? *Economic Modelling*, *24*(4), 611–635. https://doi.org/10.1016/j.econmod.2006.12.002

Hertel, T. W. (1997). *Global trade analysis: modeling and applications*. Cambridge University Press.

Huff, K., & Hertel, T. (2001). Decomposing Welfare Changes in GTAP. Retrieved from http://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=308

Hummels, D. (1999). *Toward a Geography of Trade Costs* (GTAP Working Paper No. 17). Department of Agricultural Economics, Purdue University, West Lafayette, IN: Global Trade Analysis Project (GTAP). Retrieved from https://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=1162

IPCC. (2014). Climate Change 2014: Impacts, Adaptation, and Vulnerability. In *Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Liu, B., Asseng, S., Müller, C., Ewert, F., Elliott, J., Lobell, D. B., … Zhu, Y. (2016). Similar estimates of temperature impacts on global wheat yield by three independent methods. *Nature Climate Change*, *6*(12), 1130–1136. https://doi.org/10.1038/nclimate3115

Lobell, D. B., & Asseng, S. (2017). Comparing estimates of climate change impacts from process-based and statistical crop models. *Environmental Research Letters*, *12*(1), 015001. https://doi.org/10.1088/1748-9326/aa518a

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate Trends and Global Crop Production Since 1980. *Science*, *333*(6042), 616–620.

Monfreda, C., Ramankutty, N., & Foley, J. A. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles*, *22*(1), n/a-n/a. https://doi.org/10.1029/2007GB002947

Moore, F., Baldos, U., & Hertel, T. (2017). Economic impacts of climate change on agriculture: a comparison of process-based and statistical yield models. *Environmental Research Letters*. https://doi.org/10.1088/1748-9326/aa6eb2

Moore, F. C., Baldos, U., Hertel, T. W., & Diaz, D. (2017). New Science of Climate Change Impacts on Agriculture Implies Higher Social Cost of Carbon. *Nature Communications*, *8*, 1601. https://doi.org/10.1038/s41467-017-01792-x

Nelson, G. C., & Shively, G. E. (2014). Modeling climate change and agriculture: an introduction to the special issue. *Agricultural Economics*, *45*(1), 1–2. https://doi.org/10.1111/agec.12093

Nelson, G. C., Valin, H., Sands, R. D., Havlík, P., Ahammad, H., Deryng, D., … Willenbockel, D. (2014). Climate change effects on agriculture: economic responses to biophysical shocks. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3274–9. https://doi.org/10.1073/pnas.1222465110

Porter, J. R., Xie, L., Challinor, A. J., Cochrane, K., Howden, M., Iqbal, M. M., … Travasso, M. (2014). Chapter 7: Food Security and Food Production Systems. In *Climate Change 2014: Impacts, Adaptation and Vulnerability. Working Group 2 Contribution to the IPCC 5th Assessment Report*. Cambridge, UK: Cambridge University Press.

Reilly, J., Hohmann, N., & Kane, S. (1994). Climate change and agricultural trade: Who benefits, who loses? *Global Environmental Change*, *4*(1), 24–36. https://doi.org/10.1016/0959-3780(94)90019-1

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A. C., Müller, C., Arneth, A., … Jones, J. W. (2014). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3268–73. https://doi.org/10.1073/pnas.1222463110

Rosenzweig, C., & Parry, M. L. (1994). Potential impacts of climate change on world food supply. *Nature*, *367*, 133–138.

Sacks, W. J., Deryng, D., Foley, J. A., & Ramankutty, N. (2010). Crop Planting Dates: An Analysis of Global Patterns. *Global Ecology and Biogeography*, *19*, 607–620.

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2007). *A Summary of the CMIP5 Experiment Design* (Vol. 4). Geneva, Switzerland.

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., … Asseng, S. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of Sciences of the United States of America*, 201701762. https://doi.org/10.1073/pnas.1701762114

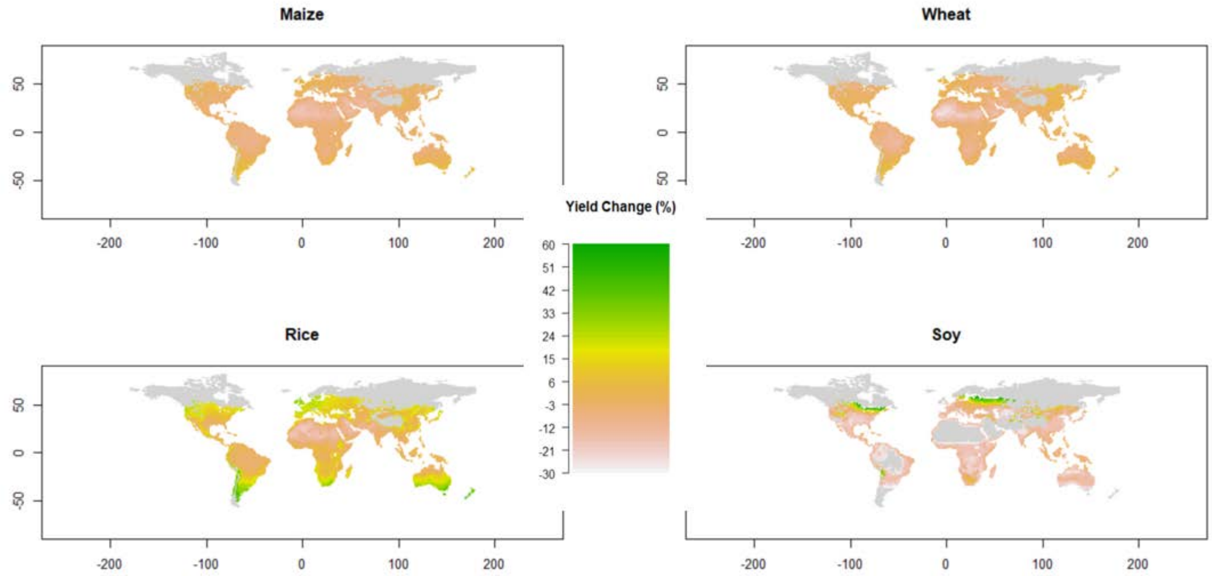

Figure 1: Global gridded yield shocks for maize, wheat, rice and soybeans at 2°C warming from Moore et al (2017a, 2017b).

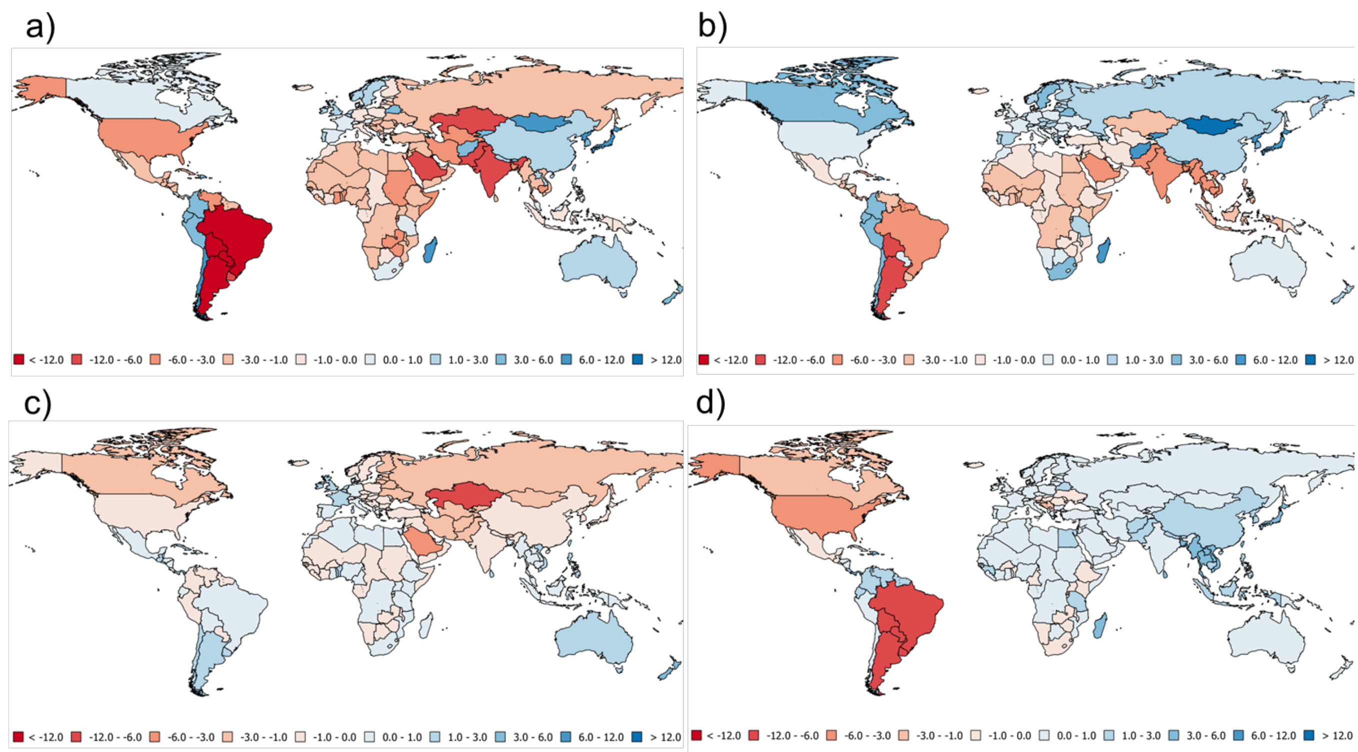

Figure 2: Decomposition of national welfare changes due to climate impacts on maize, wheat, rice and soybeans at 2°C warming.

Note: Panel A shows total direct welfare changes given climate driven yield shocks for four crops. Panels B, C and D decomposes total welfare changes given initial temperature, pattern-scaling effects and crop composition, respectively. National welfare changes are normalized by total sectoral output value of the selected crops.

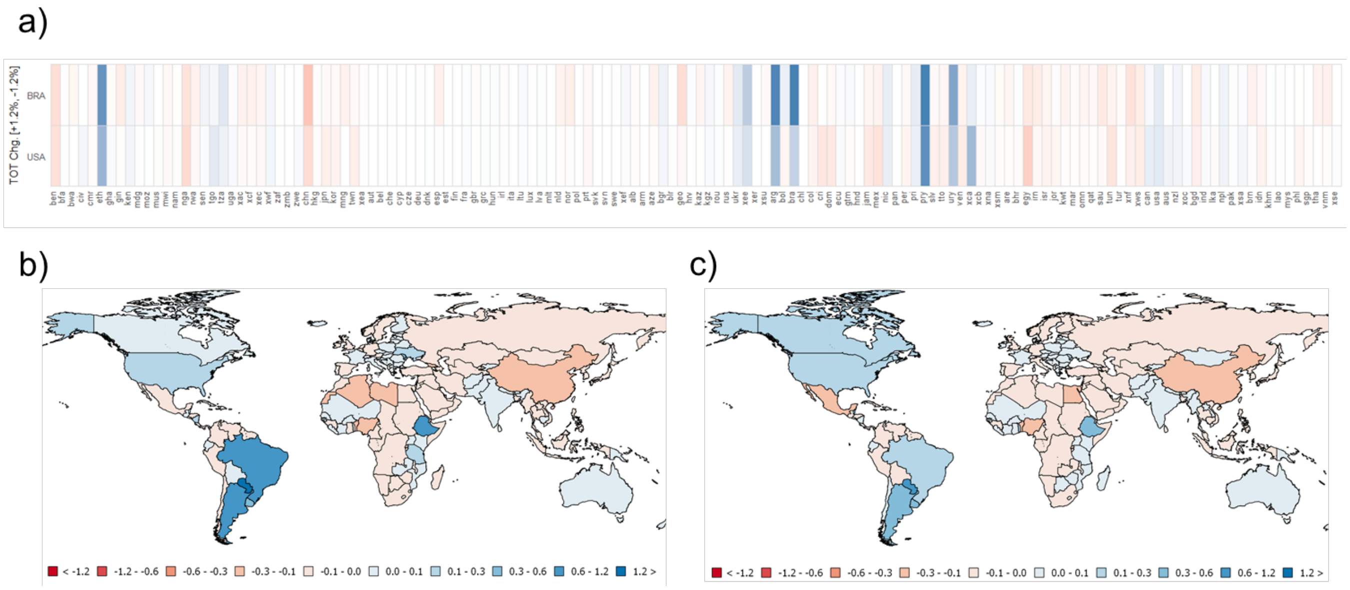

Figure 3: Regional terms of trade consequences due to climate change yield impacts in Brazil (top row in A and map B) and in US (bottom row in A and map C) only for four key crops at 2°C warming

Note: Panel A shows terms of trade changes in 140 regions (x-axis) given climate driven yield shocks in Brazil and in US only (y-axis). Panels B and C maps the same terms of trade changes in Panel A (given climate driven yield shocks in Brazil and in US only, respectively).

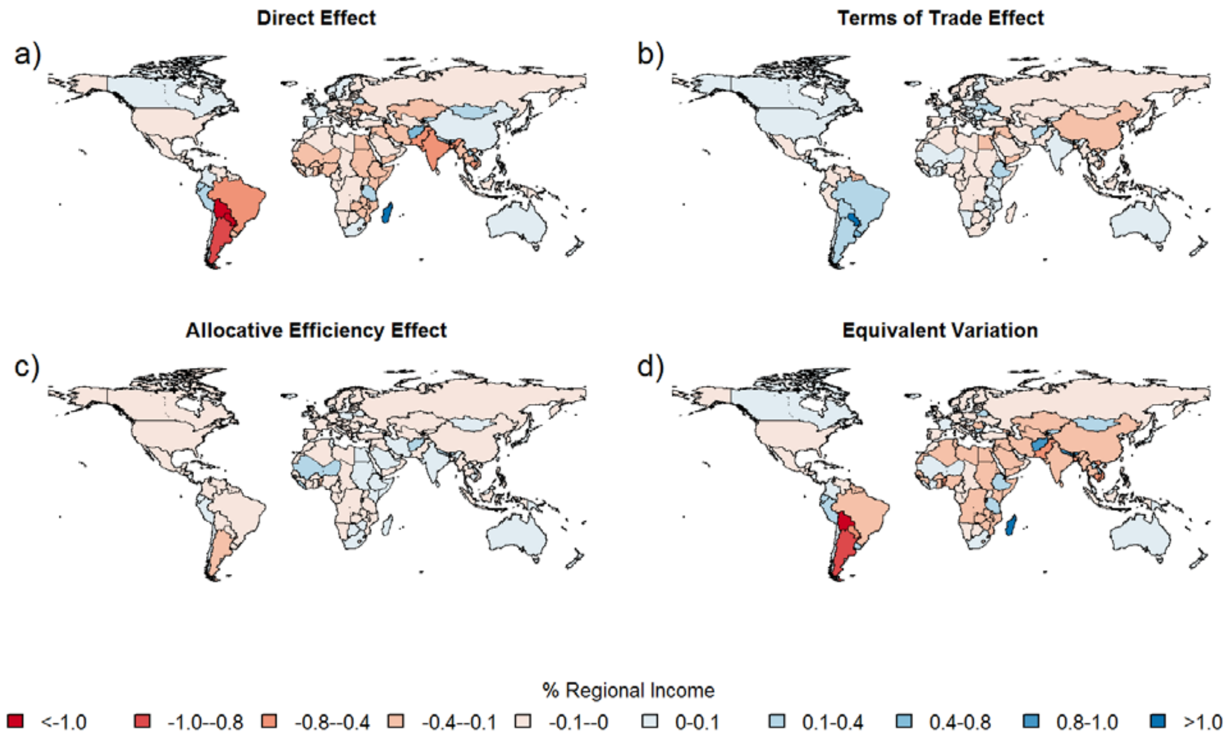

Figure 4: Overall impact of climate change on national welfare given yield shocks on maize, wheat, rice and soybeans at 2°C warming.

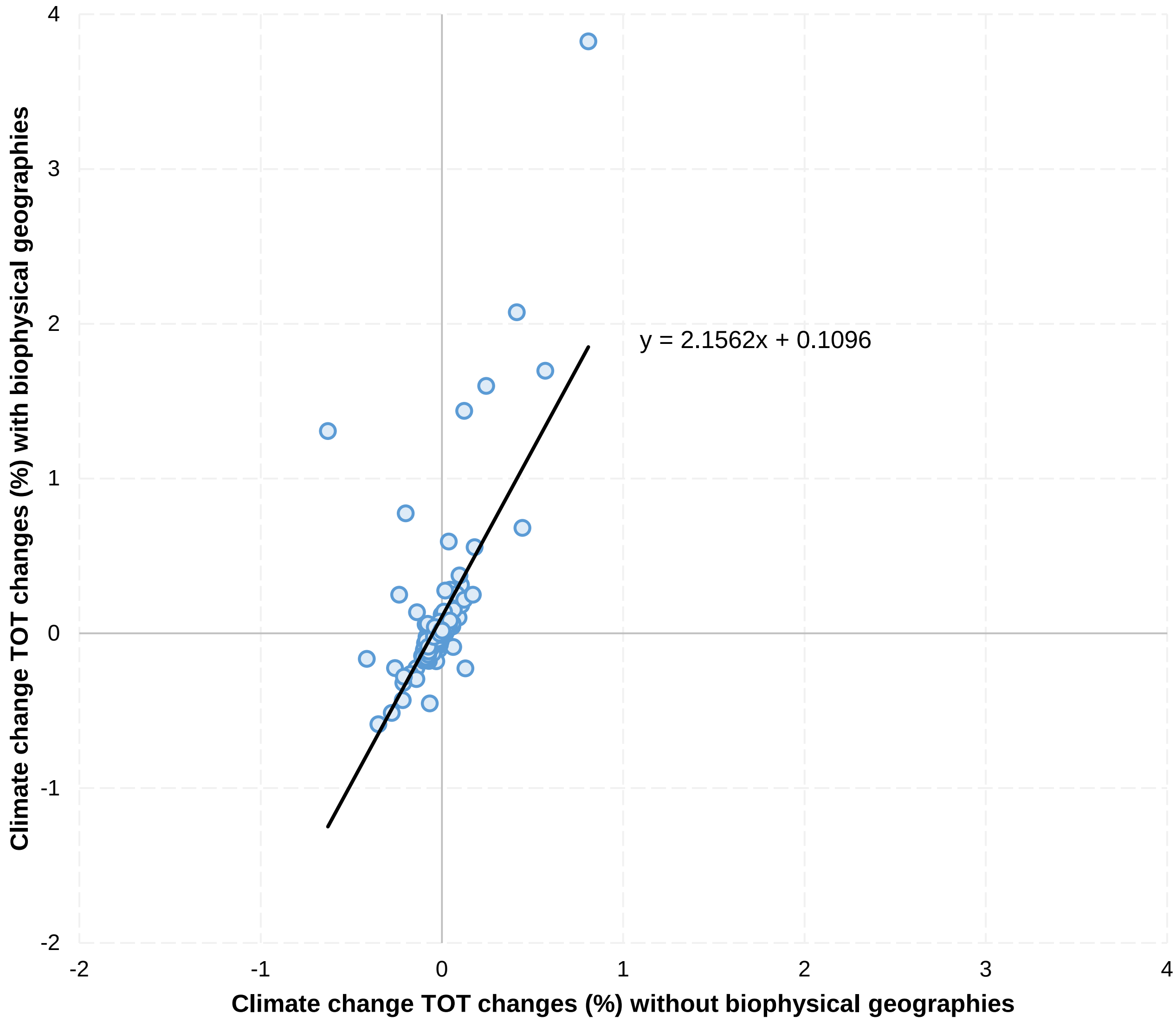

Figure 5. Terms of trade effects (% change) in the absence (x-axis) and presence (y-axis) of biophysical geographies of climate impacts on 140 world regions

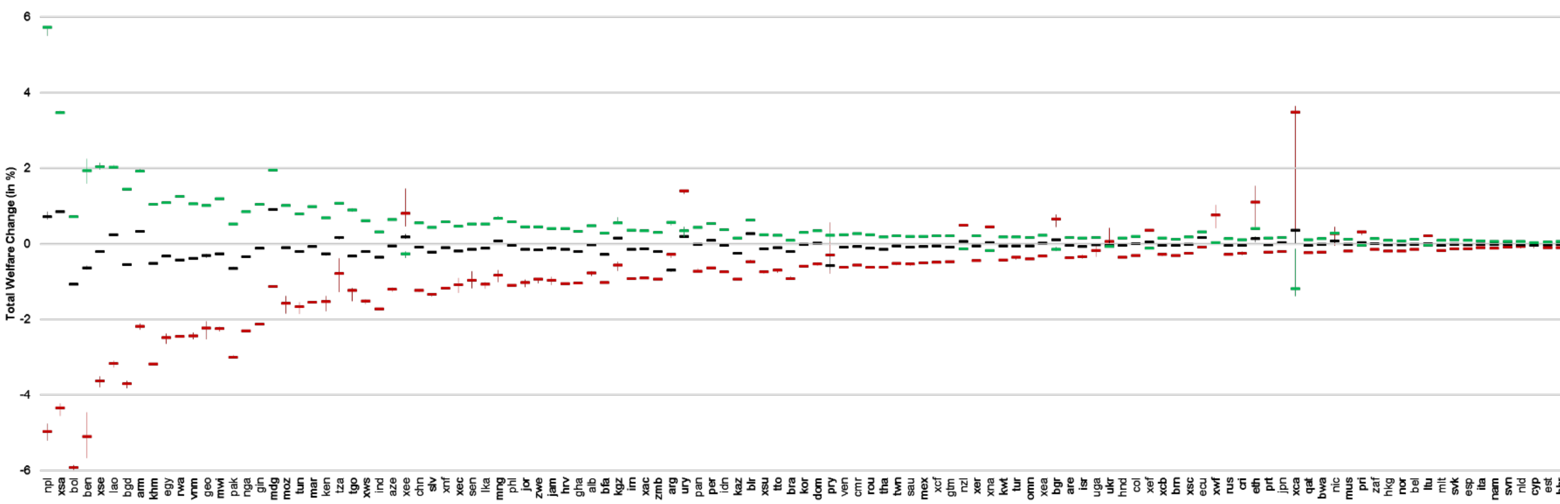

Figure 6. Regional welfare consequences of climate change impacts on four major crops (in %).

Note: Green, black and red thick horizontal bars represent welfare impacts given the crop yield shocks at 97.5, 50 and 2.5 percentile, respectively. Green, black and red thin vertical bars represent error bars in the welfare impacts due to uncertainty in trade elasticities for each corresponding crop yield shock percentiles.

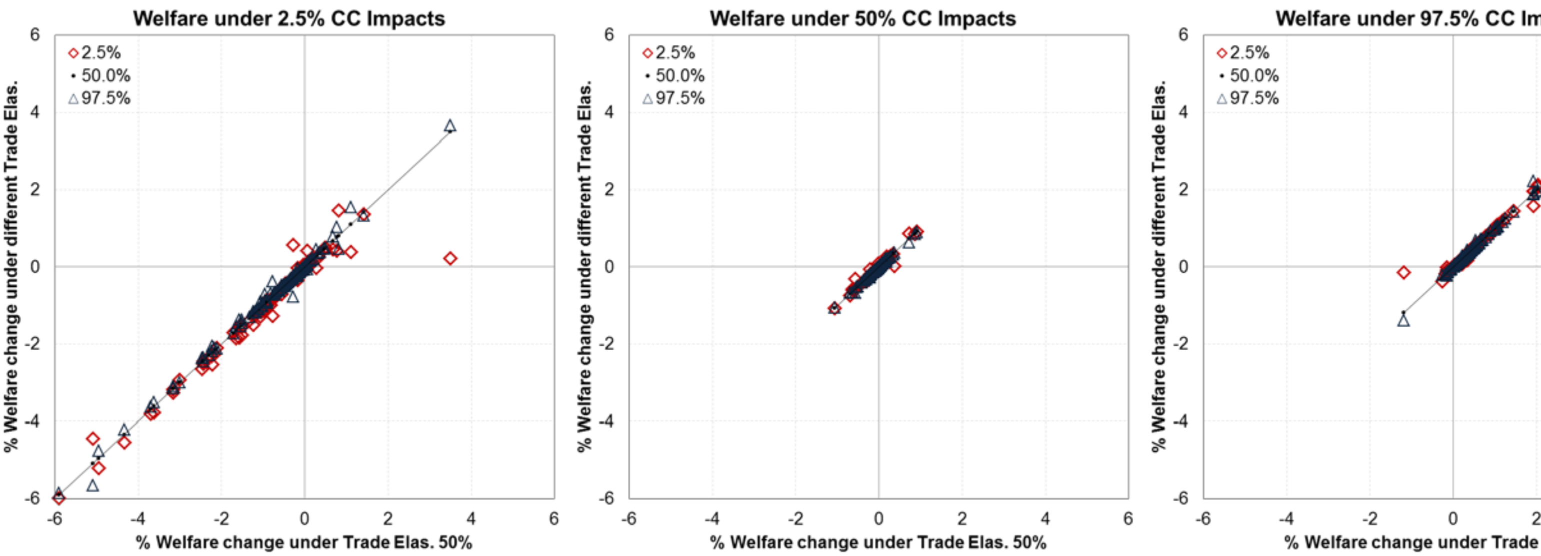

Figure 7. Scatterplot of regional welfare consequences for each trade elasticities percentile (in %) under 2.5% 50.0% and 97.5% climate impacts. Observations which depart significantly from the 45 degree line indicate a significant role for the trade elasticities.

Appendix.

Table A1. Elasticities of Substitution among Imports from Different Sources

Sector	Estimated Elasticity	Standard Deviation	Num. Obs.
Paddy rice	10.1*	4.0	26
Wheat	8.9*	4.2	32
Cereal grains nec	2.6*	1.1	131
Vegetables, fruit, nuts	3.7*	0.4	1,199
Oil seeds	4.9*	0.8	239
Plant-based fibers	5.0*	2.4	71
Crops nec	6.5*	0.4	1,796
Bovine cattle, sheep and goats, horses	4.0*	0.7	156
Animal products nec	2.6*	0.3	813
Wool, silk-worm cocoons	12.9*	2.7	76
Forestry	5.0*	0.7	529
Fishing	2.5*	0.6	527
Coal	6.1*	2.4	71
Oil	10.4*	3.8	56
Gas	34.4*	14.3	8
Minerals nec	1.8*	0.3	1,584
Bovine meat products	7.7*	1.9	211
Meat products nec	8.8*	0.9	411
Vegetable oils and fats	6.6*	0.7	717
Dairy products	7.3*	0.8	547
Processed rice	5.2*	2.6	62
Sugar	5.4*	2.0	156
Food products nec	4.0*	0.1	6,917
Beverages and tobacco products	2.3*	0.3	998
Textiles	7.5*	0.1	14,375
Wearing apparel	7.4*	0.2	9,090
Leather products	8.1*	0.3	3,457
Wood products	6.8*	0.2	4,120
Paper products, publishing	5.9*	0.2	6,597
Petroleum, coal products	4.2*	1.1	344
Chemical, rubber, plastic products	6.6*	0.1	61,603
Mineral products nec	5.8*	0.2	6,240
Ferrous metals	5.9*	0.3	5,524
Metals nec	8.4*	0.4	3,194
Metal products	7.5*	0.2	9,926
Motor vehicles and parts	5.6*	0.3	2,238
Transport equipment nec	8.6*	0.4	1,843
Electronic equipment	8.8*	0.2	8,916
Machinery and equipment nec	8.1*	0.1	44,386
Manufactures nec	7.5*	0.2	7,586

*Estimate Significant at 95% Confidence Level.

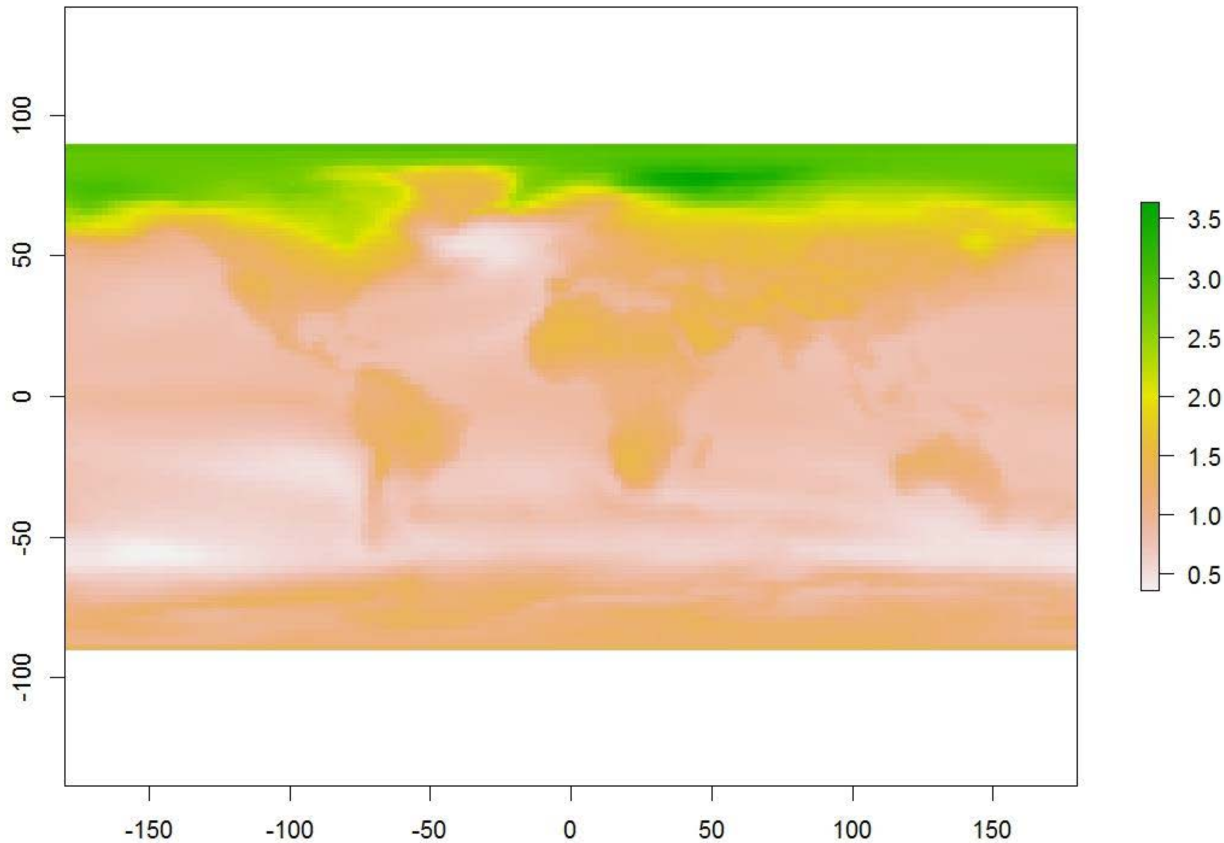

Figure A2: Pattern-scaling used in this study. This map shows the local change in temperature (Celsius) for every one degree C change in global mean temperature. It is obtained from the CMIP5 ensemble mean under RCP8.5.

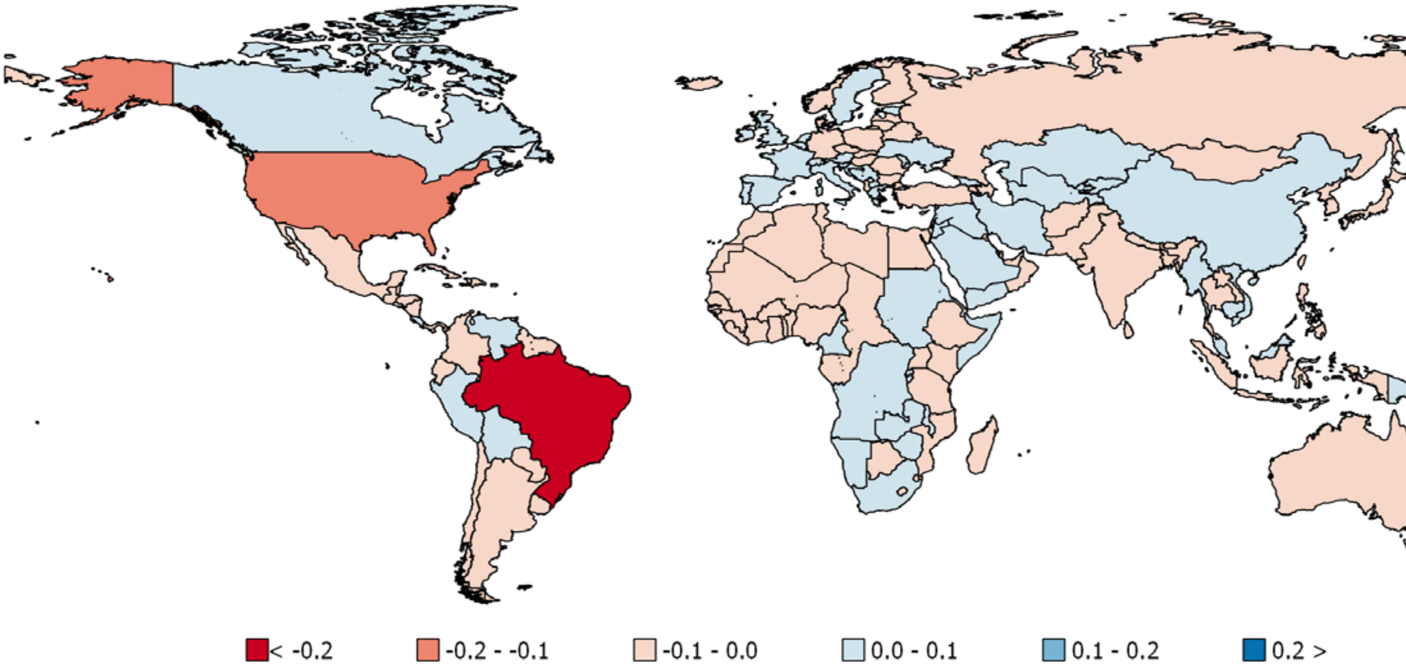

Figure A3: Regional terms of trade consequences for China due to climate change in each of the 140 countries/regions only for four key crops at 2°C warming