Understanding the Spatial Distribution of Welfare Impacts of Global Warming on Agriculture and Its Drivers

Uris L. C. Baldos, Thomas W. Hertel, and Frances C. Moore

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 role of adaptation through international trade in determining the consequences of climate change impacts. Unlike previous work in this area, instead of using a specific crop model or a set of models, we employ a statistical meta-analysis that encompasses all studies available to the IPCC-AR5 report. This permits us to isolate specific elements of the spatially heterogeneous biophysical geography of climate impacts, including the role of initial temperature, differential patterns of warming, and varying crop responses to warming across the globe. We combine these climate impact estimates with the Global Trade Analysis Project model of global trade in order to estimate the national welfare changes that 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 when we remove the spatial variation in climate impacts, the terms of trade impacts are cut in half. Given the inherent heterogeneity of climate impacts in agriculture, this points to the important role of trade in distributing the associated welfare impacts. 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. This interaction between the magnitude and heterogeneity of biophysical climate shocks and their welfare effects highlight the need for detailed representation of both in projecting climate change impacts.

Key words: Climate change, international trade, geography, welfare effects, terms of trade.

JEL codes: Q17, Q54.

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 and 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, and Costa-Roberts 2011; Rosenzweig et al. 2014; Moore et al. 2017). These studies tend to show a consistent picture of the "biophysical" geography of climate impacts

Uris L. C. Baldos is research assistant professor of agricultural economics with the Center for Global Trade Analysis, Department of Agricultural Economics, Purdue University. Thomas W. Hertel is distinguished professor of agricultural economics with the Center for Global Trade Analysis, Department of Agricultural Economics, Purdue University and Purdue Climate Change Research Center. Frances C. Moore is assistant professor in the Department of Environmental Science and Policy, University of California Davis. The authors acknowledge valuable comments by two anonymous reviewers, as well as by Dave Donaldson and other participants in the NBER workshop on agricultural trade. Hertel acknowledges the support of the National Science Foundation (RDCEP, SES-1463644), as well as USDA-National Institute for Food and Agriculture (NIFA) (IND01053G2) and Hatch (100342). Moore acknowledges support of this project by USDA National Institute for Food and Agriculture (NIFA) (award 12225279). Correspondence may be sent to: hertel@purdue.edu.

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 spatial distribution of yield impacts from climate change have been well-studied, the implications of these impacts for economic outcomes such as prices, consumption, and welfare has received less attention, despite the fact that these outcomes are of more direct interest for both adaptation and mitigation policies; (for some notable exceptions, see Reilly, Hohmann, and Kane 1994; Rosenzweig and Parry 1994; Randhir and Hertel 2000). Examining only the effects of local productivity changes could be misleading since climate change is expected to have global impacts and since many agricultural products are heavily traded internationally, making trade a critical pathway for adaptation to global warming. 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) edited 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 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. They also do not 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.

A somewhat separate strand of literature has 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). These 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." These authors' paper focuses on climate-induced changes in comparative advantage, both within and across countries. The most salient finding from their paper is that the spatial reallocation of production within countries is more important than international trade in mitigating potential losses from climate change. This point has, however, been challenged in subsequent work that lends a critical eye to model parameterization (Gouel and Laborde 2018).

A significant limitation of Costinot, Donaldson, and Smith is their reliance on a single model, that is, the United Nations Food and Agriculture Organization Global Agroecological Zones (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 it 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 bridge these different bodies of literature by focusing specifically on the interplay between the biophysical and economic geographies of climate impacts on agriculture, international trade, and economic welfare. Here we define "biophysical geography" as the spatial heterogeneity in the yield impacts of climate change owing to differences in initial temperature, changes in temperature under global warming, and differences in crops grown across the globe, and "economic geography" as the bilateral patterns of international trade which give rise to differential terms of trade effects stemming from a climate change scenario. 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 Intergovernmental Panel on Climate Change (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. Unlike Costinot, Donaldson, and Smith, we undertake explicit analysis of the interplay between uncertainties in our economic model and uncertainties in the crop impact estimates. We do not, however, model the climate impacts at a sub-national level.

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. 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 CO_2 concentrations vary by crop, and crop composition varies widely across the globe. It is for these reasons that the interregional 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 Intergovernmental Panel on Climate Change Fifth Annual Review (Moore, Baldos, and Hertel 2017; 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, including spatial variation in (a) temperature increases across the globe, (b) initial temperature (warm vs. cold regions), and (c) 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 welfare consequences of climate change.

In order to assess the interregional incidence of climate change, we employ a quantitative, global general equilibrium approach to ensure complete measurement of the welfare effects. 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, isolating the direct contribution of climate impacts on productivity from the indirect effects arising from the economic adjustments, most notably changes in the national terms of trade (ToT). In a number of cases the indirect effect reverses the sign of the welfare change from the direct (productivity) effect. 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.

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; EV) due to climate change shocks to agricultural productivity, θ_{is}, which represent the percentage 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 ($P_{is}^{O}Q_{is}^{O}$), where P_{is}^{O} is producer price and Q_{is}^{O} is output of commodity i in region s. This is summed across all sectors in region s to obtain the *direct welfare effect of climate change*. This, in turn, must be translated through the EV scaling factor (ψ_s), which is itself a function of the elasticity of expenditure with respect to utility.

$$(1)\quad EV_s = (\psi_s)\left\{\begin{array}{c} \sum_{i=1}^{N}(\theta_{is}P_{is}^{O}Q_{is}^{O}) \\ +\sum_{i=1}^{N}\sum_{r=1}^{R}(\tau_{Mirs}P_{irs}^{cif}dQ_{irs}^{MS}) \\ +\sum_{i=1}^{N}(\tau_{Ois}P_{is}^{O}dQ_{is}^{O}) \\ +\sum_{i=1}^{N}\sum_{r=1}^{R}(Q_{isr}^{MS}dP_{isr}^{fob}) \\ -\sum_{i=1}^{N}\sum_{r=1}^{R}(Q_{irs}^{MS}dP_{irs}^{cif}) \end{array}\right\}$$

The next two terms in this welfare decomposition capture how these perturbations interact with existing policy distortions when implemented globally and when prices and quantities throughout the general equilibrium systems are permitted to respond. Whenever a quantity changes in the presence of an existing distortion, a *change in allocative efficiency* results.[1] Consider, for example, what happens when the production of staple commodity i in region s is disproportionately adversely affected by climate change ($\theta_{is}<0$). Assuming that consumers seek to maintain consumption of this staple good in the face of diminished output, the country will need to import more of the product ($dQ_{isr}^{MS} > 0$), where Q_{isr}^{MS} is the bilateral flow of commodity i from r to s. If domestic producers of this commodity have been protected from foreign competitors, then there is likely to be a tariff on its importation ($\tau_{Mirs} > 0$). In this case, there will be an improvement in allocative efficiency which will contribute to increased regional welfare, as consumers access more of the product from lower cost suppliers overseas.

If domestic producers of the staple commodity receive an output subsidy, then $\tau_{Ois} < 0$, where τ_{Ois} is the ad valorem equivalent representation of this domestic "tax". In this scenario, facing an adverse climate shock, we expect output in region s to drop, *ceteris paribus*, so that ($dQ_{is}^{O} < 0$), where Q_{is}^{O} is the volume of output of commodity i in region s. The product of two negative changes results in an improvement in regional welfare, as less of the subsidized output is produced. Of course, the opposite outcome is also possible—and indeed quite likely in the Organisation for Economic Co-operation and Development (OECD) countries Costinot, Donaldson, and Smith since many of these nations lie in high latitudes and therefore might expect favorable productivity shocks from modest levels of global warming. In this case, with subsidized output rising, this particular allocative efficiency contribution to regional welfare is negative.

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 the international level. The ToT change 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 the production of region s is disproportionately adversely affected by higher temperatures, her export-weighted *fob* prices are likely to rise, relative to her import-weighted *cif* prices, $\sum_{i=1}^{N}\sum_{r=1}^{R}(Q_{isr}^{MS}dP_{isr}^{fob}) - \sum_{i=1}^{N}\sum_{r=1}^{R}(Q_{irs}^{MS}dP_{irs}^{cif}) > 0$, where P_{irs}^{fob} and P_{irs}^{cif} are the bilateral export and import prices associated with the trade flow Q_{irs}^{ms}. 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 distributional consequences 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 path taken by the model solution. We use version 9 of the GEMPACK software suite (Harrison and

[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.

Pearson 1996), 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 variable describing the change in imports, dQ_{irs}^{ms}, for example, with the levels variables, Q_{irs}^{ms}, 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 to this well-posed non-linear problem (Harrison and Pearson 1996).[2]

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, Baldos, and Hertel (2017) and Moore et al. (2017). 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's 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 1,010 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, including both biophysical growth models, as well as statistical studies of climate impacts. These are the studies 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, Ramankutty, and Foley (2008). This allows us to estimate the response of all four crops using the following:

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

where ΔY_{ijk} is the change in yield from point-estimate i for crop j in country k (in %). Further, ΔT_{ijk}, ΔCO_{2ijk} and ΔP_{ijk} are the changes in temperature (in degrees C); CO_2 concentration (in parts per million (ppm)) and rainfall (in percentage) 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 (primarily changes in crop variety and planting date). Equation (2) is estimated using an ordinary least squares regression.[3] Uncertainty in the parameters is estimated non-parametrically through 1,500 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, which is allowed to differ between C_3 and C_4 crops.[4] Finally, it allows the effect of

[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, indicating that this decomposition is well-executed.

[3] Although rainfall is included as a control in the meta-analysis, the effect of average growing-season precipitation is found to be small, relative to the effect of temperature and CO_2 fertilization, and not statistically significant (Moore, Baldos, and Hertel 2017). In addition, climate model projections of changes in average precipitation are highly uncertain (Collins et al. 2013). Therefore impacts of climate change on crop yields via precipitation are not considered further in the analysis.

[4] 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. Note that CO_2 fertilization is not considered in empirical studies and so these parameters are estimated exclusively using process-based studies.

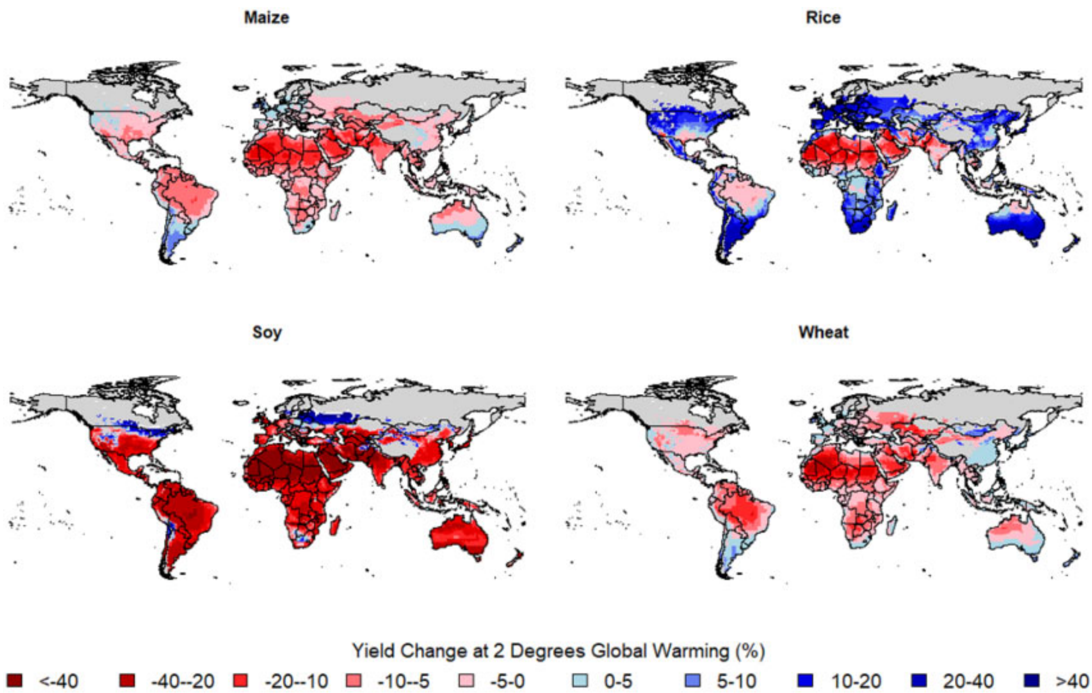

Figure 1. Global gridded yield shocks for maize, rice, soybeans and wheat at 2°C global average warming, relative to 1995-2005 average baseline

Note: Plot shows the combined effect of temperature change and CO_2 fertilization in temperate and tropical regions and are based on results of a meta-analysis of the effects of climate change on yield described in the text and in Moore, Baldos, and Hertel (2017) and Moore et al. (2017).

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), which is our preferred specification, we investigate the effects of several alternate specifications. Specifically, we: (*a*) investigate whether newer studies (publication date of 2005 or later) give a different temperature response compared to the full sample; (*b*) investigate the effect of individual agronomic adaptations, specifically changing cultivar and planting date; and (*c*) 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. (2017) 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 that this substantially increases our standard errors. The latter will be used to characterize uncertainty in climate impacts in this paper.

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, and Meehl 2012). Pattern scaling is the ratio of local warming to global average temperature change. Spatial heterogeneity in warming is driven by snow and ice melt feedbacks at higher latitudes and the different specific heat capacity of land vs. ocean, features that tend to be robust across climate models (See online supplementary 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 body of 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

Box 1. Experimental design for isolating individual contributors to spatially heterogeneous climate impacts. Experiments are ordered from least (E4) to most restrictive (E1). The contribution of each individual component is obtained by differencing experiments. For example, E4–E3 reveals the contribution of variation in initial temperature to the spatially-varying climate impacts.

E4: Full Biophysical Geography

$$\theta_{is} = \hat{\beta}_{1i}\Delta T_s + \hat{\beta}_{2i}\Delta T_s{}^2 + \hat{\beta}_{3i}\Delta T_s * \bar{T}_{is} + \hat{\beta}_{4i}\Delta T_s{}^2 * \bar{T}_{is}$$

where θ_{is} is the productivity change for crop i in region s, $\hat{\beta}_i$ are the parameters of the yield-temperature response function, estimated using the meta-analysis, $\bar{T}_{is}$ is the baseline growing-season temperature of crop i in region s, and ΔT_s is the change in temperature in region s at a global average warming of 2°C.

E3: Remove impact of initial temperature:

- Initial temperature set at mean value (neutralize starting temperature)

$$\theta_{is} = \hat{\beta}_{1i}\Delta T_s + \hat{\beta}_{2i}\Delta T_s{}^2 + \hat{\beta}_{3i}\Delta T_s * \bar{T}_i + \hat{\beta}_{4i}\Delta T_s{}^2 * \bar{T}_i$$

where $\bar{T}_i = \frac{\sum_s QO_{is}\bar{T}_{is}}{\sum_s QO_{is}}$ is the production-weighted average growing season temperature for crop s.

E2: Remove pattern-scaling of temperature

- Initial temperature set at mean value (neutralize starting temperature).
- No pattern-scaling of temperature (neutralize temperature variation)

$$\theta_i = \hat{\beta}_{1i}\,\overline{\Delta T} + \hat{\beta}_{2i}\,\overline{\Delta T}^2 + \hat{\beta}_{3i}\,\overline{\Delta T} * \bar{T}_i + \hat{\beta}_{4i}\,\overline{\Delta T}^2 * \bar{T}_i$$

where $\overline{\Delta T} = \frac{\sum_{is} QO_{is}\Delta T_s}{\sum_{is} QO_{is}}$ is the production-weighted warming at 2°C global average warming.

E1: **Biophysical Geography absent:** Uniform climate impacts on crops

- Initial temperature set at mean value (neutralize starting temperature).
- No pattern-scaling of temperature (neutralize temperature variation).
- All crop responses to climate are the same (apply production-weighted global average)

$$\theta = \frac{\sum_{is} QO_{is}\theta_i}{\sum_{is} QO_{is}}.$$

These four experiments provide a sequential decomposition of the components of spatial heterogeneity in biophysical yield impacts (figure 2). Because the temperature response functions are nonlinear, the decomposition results do depend on the order of the decomposition (e.g., the effect of pattern scaling, E3–E2, is different depending on whether baseline temperatures are first standardized, as is the case in this paper, or are heterogeneous).

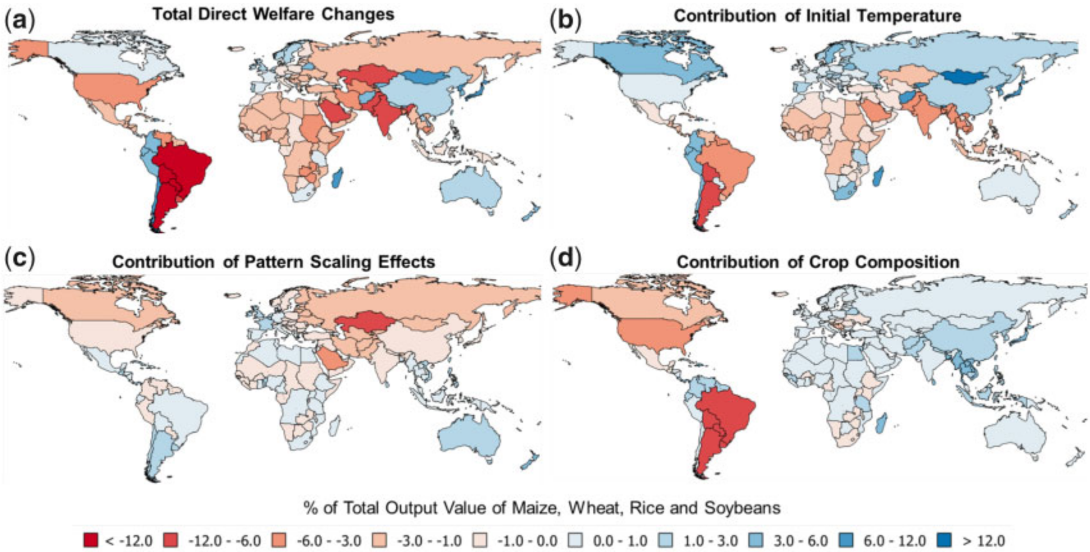

Figure 2. Sequential decomposition of national welfare changes due to climate impacts on maize, wheat, rice, and soybeans at 2°C warming

Note: Panel a) shows total direct welfare changes given climate-driven yield shocks for four crops. E4 experiment, box 1; Panel b) shows the welfare effects of initial growing season temperature. E4 experiment–E3 experiment, box 1: Panel c) shows the welfare effects of pattern scaling. E3- experiment–E2 experiment, box 1: Panel d) shows the welfare effects of crop composition. E2 experiment–E1 experiment: National welfare changes are normalized by total sectoral output value of the selected crops.

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 (*a*) initial growing season temperature and (*b*) the magnitude of local warming based on the pattern-scaling between local and global temperature change. And, since each crop responds differently to warming, the crop composition in each region will affect the aggregated direct impacts of climate change. In our analysis, we conduct a series of four experiments to isolate the contribution of each of these drivers of the geographic pattern of yield shocks (see box 1). The full effects are captured in our baseline experiment (E4). Next, we standardize the temperature shock by replacing the temperature change in each location with the area-weighted average temperature change for each crop. This experiment (E3) 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 (E4-E3), 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 (E2). Deducting the resulting welfare change from the previous (no pattern scaling) welfare, we obtain the effect of initial temperature on direct welfare impacts (E3-E2). 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 (E1). Deducting welfare by region from the prior result (E2-E1) gives us the impact of crop composition on the direct welfare effects of climate change by country.

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.[5] 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 that are the focal point of this paper.

The GTAP model runs on any desired aggregation of the GTAP database, now in its 9th release (Aguiar, Narayanan, and McDougall 2016), which contains the most comprehensive set of fully integrated, globally exhaustive information on agricultural production, consumption, trade, tariffs, and domestic agricultural policies.[6] Version 9.1 of the database, which is used here, disaggregates the 2011 global economy into 140 regions—of which 120 are individual countries for which primary data have been assembled, reconciled, and integrated into the overall database. 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, Narayanan, and McDougall 2016). Reconciled bilateral merchandise trade data are obtained using the methodology outlined in Gehlhar (1996).

As we will see in the results section, parameterization of the model is critical to our results—particularly the Armington elasticities of substitution between imports from different sources (commonly referred to as the "trade elasticities"). These elasticities, along with the bilateral import shares, govern the "geography" of international trade and the potential for adjusting that geography in response to climate shocks. As noted by Hillberry and Hummels (2013) in their contribution to the Handbook of CGE Modeling: "It is no exaggeration to say that the trade elasticity is the most important parameter in modern trade theory …… It is critical to evaluating welfare gains." These authors go on to admonish other authors for simply "taking elasticities from the literature" without careful consideration. Indeed, Hillberry and Hummels argue that these elasticities should be identified using the same type of variation in both the estimation and the simulation of trade impacts. We adhere to their admonition and have chosen to draw on the work of Hertel et al. (2007), who estimate equation (3) using a cross-section of five-digit, SITC customs data compiled by Hummels (1999) for six importers in the Americas and New Zealand, giving rise to 187,000 observations on both *fob* and *cif* values:

$$\text{(3)}\quad \begin{aligned}\ln V_{irs} = {} & a_0 + a_{is} + a_{ir} \\ & + \beta_{0,i} \ln\left(1 + freight_{irs}\right. \\ & \left. + tariff_{irs}\right) + \beta_{1,i} \ln Dist_{rs} \\ & + \beta_{2,i} Lang_{rs} + \beta_{3,i} Adj_{rs} + \varepsilon_{irs}.\end{aligned}$$

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*, the 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. This is well-suited to the current study since the identification strategy is based on long run price variation induced by differences in transport costs and tariffs. This is appropriate for analysis of the consequences of climate change over the long run.

Equation (3) is estimated using pooled, ordinary least squares in which the OLS estimates of $\beta_{0,i}$ are constrained to be equal for all five-digit categories within a given GTAP merchandise sector (of which there are 40). Estimates for the crops sectors of interest in this study (see supplementary appendix 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 pooled OLS standard error associated with each estimate. This will facilitate our

[5] Refinements and extensions of the standard model are available here: (https://www.gtap.agecon.purdue.edu/resources/tech_papers.asp).

[6] Documentation and downloads of the data is available here: (https://www.gtap.agecon.purdue.edu/databases/v9/default.asp),

subsequent analysis of the sensitivity of model results to parametric uncertainties.

Results

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

Biophysical geography of climate impacts. We begin with the direct effect of climate change on regional welfare from equation (1): $EV_{direct,s} = (\psi_s)\{\sum_{i=1}^{N}(\theta_{is}P_{is}^{O}Q_{is}^{O})\}$. As previously noted (box 1), 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 the following: differences in initial temperature, differential rates of warming, 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, that is, $\{\sum_{i=1}^{4}(P_{is}^{O}Q_{is}^{O})\}$ 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 Celsius 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 using the experimental design laid out in box 1. 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 2, panel C 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 Celsius 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 via the indirect effects? 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, $EV_s = (\psi_s)\ \{\sum_{i=1}^{N}\sum_{r=1}^{R}(Q_{isr}^{MS}dP_{isr}^{fob}) - \sum_{i=1}^{N}\sum_{r=1}^{R}(Q_{irs}^{MS}\ dP_{irs}^{cif})\}$, 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, the 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 individual 140 countries one-at-a-time and record the impacts on each of the

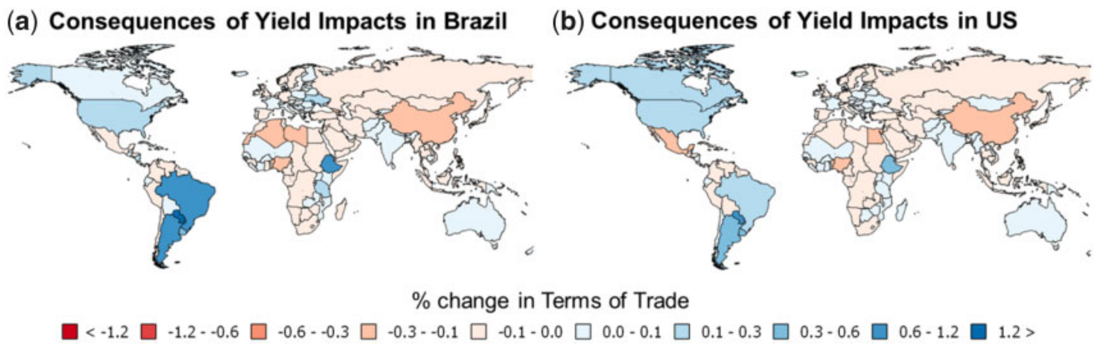

Figure 3. Regional terms of trade consequences due to climate change yield impacts in Brazil only, (Panel a) and in the United States (Panel b) only, for four key crops at 2°C warming

140 countries' terms of trade for each of these national perturbations. 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, Horridge, and Pearson (2000) discovered a solution which has been implemented into the GEMPACK software used in this paper (Harrison and Pearson 1996; Harrison, Horridge, and Pearson 2000). 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 of a single, global climate change experiment.[7]

Figures 3(a) and (b) map the elements of the Brazil and U.S. rows across the world. Consider figure 3a, 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 United States, as a soybean competitor with Brazil, also gains from the Brazilian climate shocks. Figure 3b shows a similar map, only this time reporting the subtotals pertaining to the U.S. climate shocks. As U.S. competitors, Canada, Brazil, and Argentina gain, while those importing U.S. agricultural products (e.g., Mexico and China) 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 online supplementary appendix figure A4 for an example). Figure 4b shows the aggregate terms of trade effects for each region.

The third, and final, element of the global geography of climate impacts is the allocative efficiency component of equation (1), $EV_s = (\psi_s)\{\sum_{i=1}^{N}\sum_{r=1}^{R}(\tau_{Mirs}P_{irs}^{cif}dQ_{irs}^{MS}) + \sum_{i=1}^{N}(\tau_{Ois}\ P_{is}^{O}dQ_{is}^{O})\}$. This is mapped, for the world, in figure 4c, and 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 database, 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 interactions between changes in bilateral trade and tariffs and between changes in output of agricultural products and domestic support policies. A particularly interesting case is that of China, where soybean production is heavily subsidized. As climate change reduces soybean output in the United States, Brazil, and Argentina, world prices rise, and China is

[7] Online supplementary appendix figure A3 provides a slice of this matrix wherein 2 x 140 matrix is presented, with the cells shaded to reflect gains (blue) and losses (red), evaluated as a percentage change in 140 countries' overall ToT as a consequence of climate shocks in the USA and in Brazil, respectively.

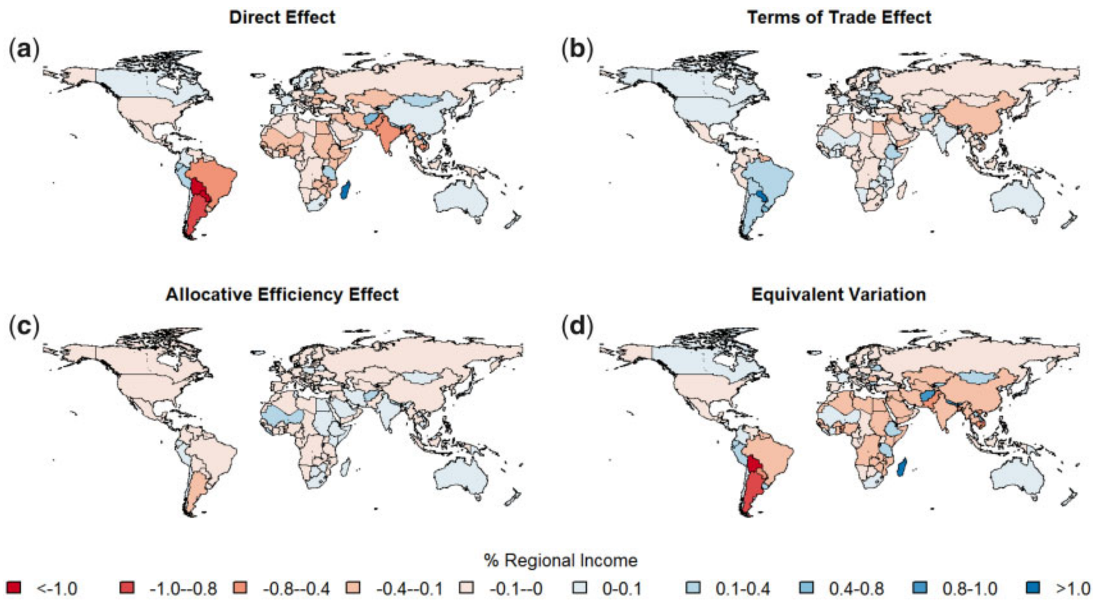

Figure 4. Overall impact of climate change on national welfare given yield shocks on maize, wheat, rice, and soybeans at 2°C warming

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 4c.

Interactions between biophysical and economic geographies. How do 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 (recall E1 in box 1). Figure 5 plots the terms of trade effects arising from this simulation (E1: no biophysical geography = horizontal axis) against those arising from the full geography simulation (E4: full spatial heterogeneity = 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 more pronounced (more than double, on average) when the full biophysical geography is present. In other words, absent spatial variation in climate impacts on these staple crops, there is far less of a role for economic geography as reflected in the pattern of bilateral trade amongst these 140 different trading regions. Thus, the biophysical and economic impacts of climate change reinforce one another. This highlights the importance of combining sophisticated analyses of spatial variation in climate impacts with more sophisticated empirically estimated models of bilateral trade flows. However, in the past, the more sophisticated treatments of climate impacts have been combined with relatively simplistic models of trade (e.g., the integrated assessment literature) and the sophisticated trade models have been combined with relatively simplistic treatments of climate impacts (e.g., Costinot, Donaldson, and Smith 2016).

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

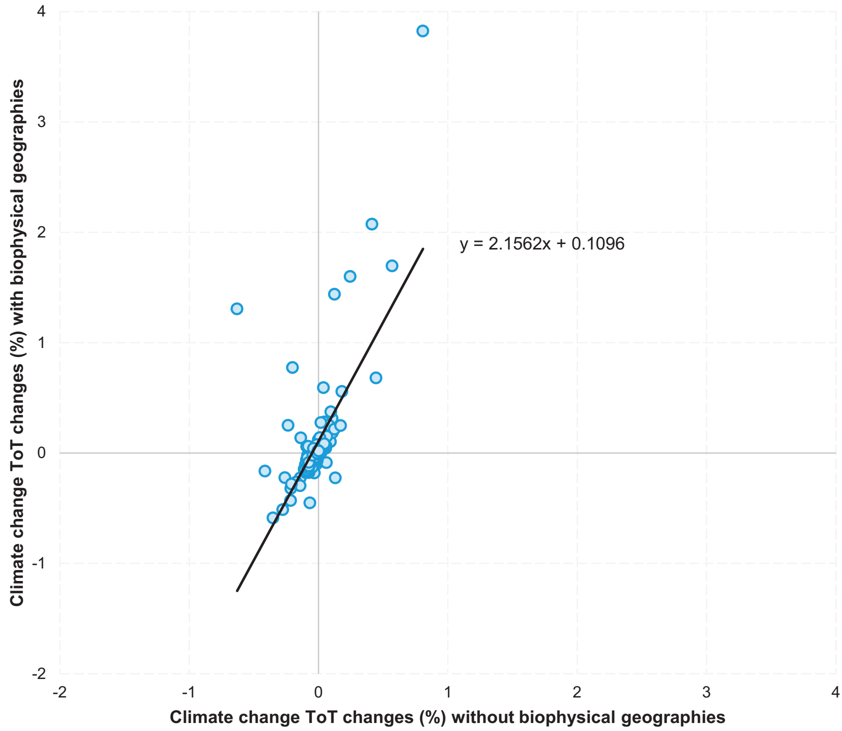

Figure 5. Terms of trade effects (percentage change) in the absence (x-axis) and presence (y-axis) of biophysical geographies of climate impacts on 140 world regions

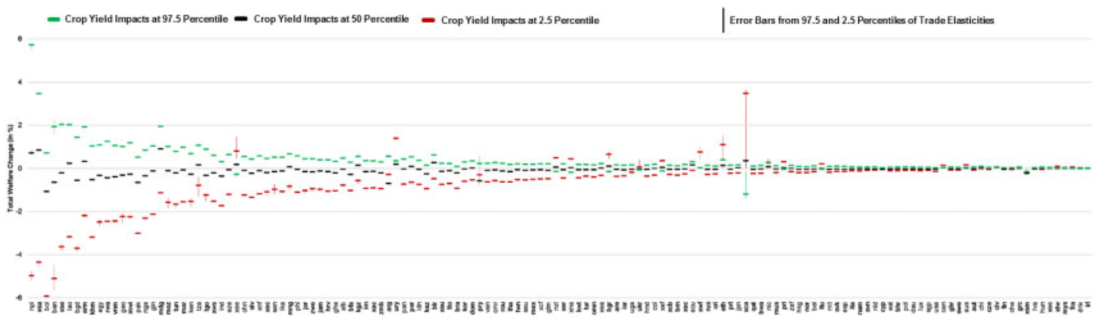

Figure 6. Regional welfare consequences of climate change impacts on four major crops (percentage of expenditures on all goods and services)

Note: Upper, middle and lower 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 using 97.5 and 2.5 percentile values for each corresponding crop yield shock percentiles. This uncertainty is mostly small for many of the regions and so these error bars are only visible for a subset of points.

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 bars 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), using the median estimates of trade elasticities. That is, we run the model three times, each time changing the size of the climate impacts on the four

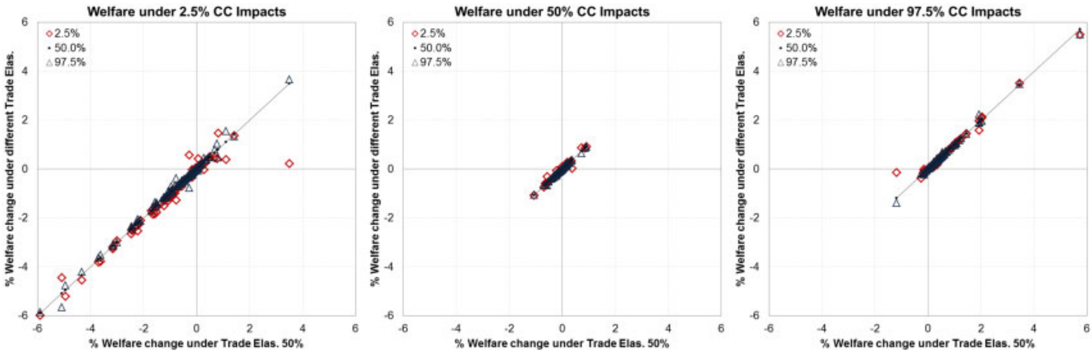

Figure 7. Scatterplot of regional welfare consequences for each trade elasticities percentile under 2.5% 50.0% and 97.5% climate impacts

Note: Observations which depart significantly from the 45-degree line indicate a significant role for the trade elasticities.

staple crops, once with the impacts drawn from the left tail of the distribution (low yields), once from the median, and once from the right-hand tail (high yields). Through each of these point estimates runs an "error bar" reporting the welfare change extending from the estimates with low to high values of estimated trade elasticities—hence the need for nine total simulations—though these error bars are very small and therefore not visible for many of these regions and runs. Several points are immediately evident. Firstly, the median impacts—that is, the impacts evaluated at median yield and trade elasticities—are mostly negative but are modest in size. Secondly, the welfare impacts of biophysical uncertainty are asymmetric. At high yields, the positive welfare deviations from the mean impacts are far smaller than the negative welfare changes induced by drawing from the low end of the yield distribution. This is partly a result of asymmetric uncertainties in the yield response function (which are determined non-parametrically using a block-bootstrap procedure), but is exacerbated by the disproportionate welfare effects of very adverse productivity shocks. This underscores the significant 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 risks stemming from biophysical uncertainties are further compounded by the uncertainties in the trade elasticities. These too, have an asymmetric impact on welfare. With a few exceptions, the welfare impact of varying the trade elasticities is larger 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 contains three points for each of the 140 regions in the trade model, each of the three pertaining to different values of the trade elasticities (low, medium, and high). Each panel refers to a different draw from the biophysical impacts distribution. The first panel corresponds to the most adverse climate impacts (2.5 percentile). Here we also see the largest spread of welfare impacts. The second and third panels refer to the modal (50th 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 (97.5th percentile), most regions tend to gain, while the low draw (2.5th percentile) results in the majority of countries losing from the climate impacts on these 4 major crops.

The scatterplot in each of the panels in figure 7 plots the welfare change under the modal trade elasticity (50th percentile), against that obtained from simulating the model with the low (2.5th percentile = red diamonds), medium (black dots), and high (97.5th 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, a measure of the importance of varying trade elasticities in driving welfare effects. 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, again demonstrating the fact that trade plays a particularly important role in determining welfare consequences in the presence of large productivity shocks.

Discussion and Limitations

Climate change will have spatially-heterogeneous effects on agricultural productivity around the world, determined by geographic factors such as the pattern of global warming and initial growing-season temperatures. But the welfare consequences of these shocks is partly determined by the economic geography of the agricultural trade network, shaped by trade costs and historical trading relationships. Here we provide a decomposition of the welfare consequences of climate change impacts in agriculture and demonstrate the important interaction between these two geographies: the more climate change shifts comparative advantage rather than simply changing aggregate productivity, the larger the role of trade in determining welfare outcomes. Moreover, the ability of the trade network to adjust in response to climate change impacts, determined by trade elasticities, is particularly important for large and negative productivity shocks.

However, there are important limitations of this study. First and foremost is its limited coverage of the food system. While the four crops included here account for a very large share of global calorie consumption, many other crops are also likely to be affected by climate change. Unfortunately, there are insufficient studies—either empirical or modeling based—to permit us to undertake a meta-analysis of these impacts. In the future, it will be important to extend our meta-analysis to more crops. In addition, we expect that the livestock sector will be affected by global warming (McCarl and Hertel 2018) and this may have important impacts, in turn, for the derived demand for feedstuffs. Finally, the fisheries sector is expected to experience negative impacts—particularly in the tropics (IPCC 2014). Any comprehensive analysis of the welfare consequences of climate impacts on food security must address all of these pathways.

A more specific limitation of this work is the fact that we have modeled farmer responses to climate change at the national 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.

Another important limitation—and one that is shared with the Costinot, Donaldson, and Smith study—is that we impose future climate change on the current economy. While projecting the global economy forward over the twenty-first century is conceptually appealing, it is fraught with challenges—particularly in the context of global general equilibrium modeling in which there are roughly one-half million bilateral trade flows. Furthermore, as Cai, Golub, and Hertel (2017) highlight in their study of optimal agricultural R&D investment, the uncertainties in population and income growth, and the economic responses to these global drivers, dwarf the impacts of climate change on agriculture over the coming century. We prefer to hold the economic environment constant, while examining the impact of climate change on agriculture. This allows us to systematically explore the climate impact uncertainties, as well as the uncertainties in trade response to these shocks, and their interactions.

Our investigation of the interplay between the terms of trade effects (economic geography, as reflected in bilateral trade patterns) and the biophysical (direct) impacts of climate change has important implications for future research in this area. Firstly, it demonstrates the important role of international trade in climate change adaptation—particularly for agricultural commodities. We show that the geography of climate impacts is inextricably interwoven with the geography of international commodity flows: removing one renders the other less relevant. In particular, as we remove the sources of spatial heterogeneity in the direct impacts of climate change, the indirect impacts—as mediated through international trade—also diminish in importance. This has important implications for those studying the economic and food security consequences of global climate impacts on agriculture that can be broken into two strands. The most sophisticated work on climate impacts builds heavily on the AgMIP community and devotes great attention to the spatial distribution of climate impacts and associated uncertainties. However, in this community, trade modeling receives relatively less attention. The second strand of research, coming largely from the international trade literature, entails relatively simplistic treatments of climate impacts, but has a more sophisticated empirical approach to trade modeling. Our findings suggest that both are needed in order to obtain an accurate picture of the spatial distribution of welfare changes owing to climate impacts in agriculture.

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 these impacts. It does so by bridging the extensive body of 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 that 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 spatial distribution of climate impacts, including the role of initial temperature, differential patterns of warming, and differential crop responses to 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 spatial variation in biophysical impacts, 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 variation in trade elasticities in the presence of yield outcomes at the lower end of the climate change impacts distribution.

Supplementary Material

Supplementary materials are available at *American Journal of Agricultural Economics* online.

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