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Agricultural Climate Change Adaptation: A review of recent approaches

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Abstract

The impact of climate change on agricultural outcomes depends on the responses of economic agents. But these adaptations are the result of complex optimization decisions and general equilibrium dynamics, and thus are difficult to measure. This report reviews two recent approaches to studying climate change adaptation in agriculture: panel data methods and spatial general equilibrium models.

Keywords

Climate change, agriculture, adaptation, spatial general equilibrium models, trade models.

JEL Classification Numbers

F18, Q15, Q17, Q51, Q54, Q56

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Contents

1. Introduction

Estimating the impact of climate change on food production is not straightforward. Overall, a warming climate appears to have a negative impact on yields of maize, wheat, rice and soybeans (Field et al., 2014). However, increasing temperature is not the sole metric of climate change; other relevant changes in climatic systems include shifts in precipitation conditions, extreme weather and atmospheric composition (Stocker et al., 2013). The interaction of these physical processes will directly impact agricultural outcomes.

This link is further complicated by adaptation, or the response of economic agents to realized or expected climate change.[1] Consumers, producers and governments may respond to climate change by, for example, adjusting production technologies, improving institutional capacity or participating in global food systems. Accounting for these adjustments is central to accurately estimating the impact of climate change on agricultural outcomes. However, it is often difficult to measure the role of adaptation within these causal chains.

The definition of climate change adaptation is purposefully vague and encompasses a host of different activities.[2] Occasionally, these activities are explicit, discrete actions; for example, a farmer may experience several seasons of elevated temperatures and choose to plant heat-resistant seed varieties. But the identification of seemingly explicit climate change adaptation is not straightforward, as these reponses are the result of heterogeneous agents making complex optimization choice. Further, many adaptive actions may be implicit responses to changing conditions.[3] For example, a region experiencing higher temperatures may shift labor away from agriculture and begin relying on imported food to meet its needs. In either case, estimating adaptive behavior from observed data is empirically complicated and prone to endogeneity concerns, as will be discussed in the next section.

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[1] Economists may define adaptation slightly differently than scientists or policy makers. It is common in policy realms for resilience and adaptation to be defined separately; see Walker and Salt (2006), who define resilience as encompassing adaptation (specifically, resilience comprises resistance, adaptation and transformation). Economists tend to conflate the definition of resilience and adaptation. See Fankhauser (2017) for a discussion on this.
[2] To illustrate this, see the list of adaptation options in Field et al. (2014), table 14-1.
[3] Some subsets of the literature have attempted more detailed taxonomies of adaptation. For example, Burke and Lobell (2010) distinguish between autonomous and planned adaptation. However, as discussed in Fankhauser (2017), classifying any adaptation as autonomous is a misnomer, as “autonomous” adaptation is the result of complex optimization decisions made by multiple agents. Overall, specificity is required when discussing adaptation strategies.

In this report, I review recent approaches to studying agricultural climate change adaptation. I consider two broad methodologies. The first of these is panel data techniques, which use available weather data to identify whether adaptations have occurred. I then consider spatial general equilibrium models, which can be used to predict future adaptive behaviors. My intention is to provide the reader with a clear overview of how these tools have been used to study agricultural climate change adaptation, a discussion of the benefits and limitations of these approaches, and a list of resources that can be consulted for future inquiries.

Before proceeding, I would like to make a few clarificatory points. First, this review will generally focus on the response of agents to rising temperatures. As noted above, this is far from the only climate change metric. However, recent innovations in the agricultural adaptations literature outlined in this report specifically estimate responses to increasing temperatures.

Second, it's worth mentioning that the approaches reviewed differ from each other in meaningful ways. Both panel data methods and spatial general equilibrium models estimate the adaptive behaviors arising from heterogeneous agents making complex optimization choices. But panel data methods are often retrospective, estimating past adaptive behavior from observed data. In contrast, spatial general equibirum frameworks attempt to model expected responses to predicted climate outcomes. Thus, the methods discussed below differ both in purpose and in scope.

Finally, spatial general equilibrium models may be seen as a subset of recent advances in macroeconomic climate change analysis. Structural models that account for dynamics or general equilibrium effects have become powerful tools in climate change research. This review focuses on a small subset of this literature that specficially pertains to agricultural adaptations. As such, I do not touch on some key innovations in this field.[4] Nevertheless, I hope this review provides a concrete introduction to one dimension of this evolving toolkit.

I begin by discussing the role that agricultural adaptive behaviors have played in climate impact assessments and the development of panel data methods for studying these behaviors. I then review the use of spatial general equilibrium models in studying adaptive behaviors in agriculture.

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[4] For work that focuses on bridging the gap between macroeconomic and microeconomic climate analysis, see Bakkensen and Barrage (2020, 2021). For an example of quantitative macroeconomics being used to model adaptation behaviors, see Fried (2021).

2. Impact assessments and adaptation

Insights about climate change adaptation are often closely tied to studies that estimate the effect of changing temperature on agricultural outcomes (Fankhauser, 2017).[5] For example, consider early impact assessments that employ the so-called "production function" approach. These studies use carefully constructed production functions to estimate the physical response of, say, crop yields to increased temperatures. However, these estimates assume farmers do not adapt any aspect of their production process to changing temperatures, and the assessments may therefore be biased by basic adaptation strategies, such as switching crop varieties. For this reason, the production function approach is sometimes called the "dumb-farmer approach" (Schneider et al., 2000).

The Ricardian approach developed by Mendelsohn et al. (1994) addresses this criticism. Instead of measuring the impact of temperature on agricultural yields, this seminal paper uses cross-sectional data to estimate the impact of temperature on the value of farmland. The authors assume that the value of farmland reflects the best possible use of land, and that farmers have perfect knowledge of this best-use value function. This is an improvement over the production function approach, as the best-use value function implicitly accounts for adaptations such as alternative crop production or substitution of inputs. In practice, the authors use cross-sectional data on agricultural outcomes (y_i), climatic variables ($\mathbf{c}_i$) and agricultural inputs and controls ($\mathbf{x}_i$) for various regions to estimate the following:

$$y_i = \alpha + \beta \mathbf{c}_i + \gamma \mathbf{x}_i + \epsilon_i \tag{1}$$

Here, α is a constant, and ϵ_i is the unobserved prediction error. This specification is identified under the "unit homogeneity" assumption (Hsiang, 2016).[6] Unfortunately, however, this assumption is not always plausible and is prone to endogeneity concerns. For instance, temperature may be correlated with unobserved characteristics like institutional quality (Acemoglu et al., 2002). As such, the specification may be vulnerable to omitted variable bias. In addition, this method merely accounts for adaptation; it does not attempt to measure it explicitly.

[5] The review of the impact assessments literature in this section follows Hsiang (2016) and Fankhauser (2017).
[6] The identifying assumption is that differences in output between areas with the same characteristics/inputs ($\mathbf{x}$) are driven solely by differences in climate. Hsiang (2016) describes this assumption as "unit homogeneity."

To address endogeneity concerns, climate econometricians began incorporating panel methods into their impact assessments. In addition to providing more plausible identification assumptions, panel methods enable researchers to estimate adaptation efforts. To explicitly measure adaptation instead of just accounting for it, climate economists have recently turned to structural models and general equilibrium analysis.

3. Panel methods

Deschênes and Greenstone (2007) took the endogeneity concerns associated with the Ricardian approach seriously. Their impact assessments measured the response of land values to changes in weather over time by estimating the following specification:

$$y_{it} = \alpha_i + \theta_t + \beta_{FE}\mathbf{c}_{it} + \gamma\mathbf{x}_{it} + \epsilon_{it} \tag{2}$$

Here, α_i are region-fixed effects and θ_t are time-fixed effects.[7] Regional-fixed effects account for unobserved heterogeneity that is constant over time. Therefore, α_i corrects for some of the omitted variable bias present in the cross-sectional specification (1). Naturally, the fixed-effects approach may still be vulnerable to endogeneity concerns.[8] In addition, the approach in (2) estimates the expected response of variable y to marginal changes in *weather*, conditional on region- and time-fixed effects. But weather is not the same thing as climate; if we wish to estimate the impact of climate change on outcomes, we must assume that this is equal to the expected response of y to changes in *climate*. Thus, the fixed-effects approach relies on the assumption that response to short-run changes in weather are comparable to the response to changes in climate.[9]

Long differencing serves as a compromise between the cross-sectional and fixed-effects approaches. Variables are averaged over two distinct periods in time (t_1 and t_2). The impact is thus estimated from differences in averages over the two time periods:

[7] I focus on region- and time-fixed effects for notational simplicity. In practice, Deschênes and Greenstone (2007) include county and state time-fixed effects in their preferred specification. In general, two-way fixed effects may be included.
[8] For example, weather data are collected from weather stations that may have differences in coverage due to exogenous policy shocks. If the availability of weather data and economic outcomes is correlated, results may suffer from attenuation bias. See Auffhammer et al. (2013) for a discussion on this.
[9] Hsiang (2016) calls this the marginal treatment comparability assumption, and notes that this assumption is weaker than the unit homogeneity assumption necessary in (1).

$$\bar{y}_{i,t_2} - \bar{y}_{i,t_1} = \alpha_i + \beta_{LD}(\bar{\mathbf{c}}_{i,t_2} - \bar{\mathbf{c}}_{i,t_1}) + \gamma(\bar{\mathbf{x}}_{i,t_2} - \bar{\mathbf{x}}_{i,t_1}) + \epsilon_i \tag{3}$$

This method estimates the impact of long-term changes in climate using the cross-sectional correlations.

None of the methods discussed so far attempts to explicitly measure adaptation. Both of the time-series specifications above are used to estimate response functions; the coefficients of interest, β_{FE} and β_{LD}, each estimate how agricultural outcomes respond to temperature. But the estimated responses are calculated from different variations in the data. The fixed-effect coefficient, β_{FE}, is estimated from short-run variation in weather, whereas the long-differences coefficient, β_{LD}, is estimated from short- and long-run responses to weather.

Burke and Emerick (2016) use this distinction to derive insights about adaptation. If farmers do not adapt to long-run changes in weather, then the response of crop outcomes to weather in the short run would be the same, suggesting that $\beta_{LD} = \beta_{FE}$. If farmers adapt to long-run changes in weather, then one would expect that the impact of weather on outcomes could be mitigated somewhat in the long run. This would suggest that β_{FE} is larger than β_{LD}.[10] Burke and Emerick use this insight to define an adaptation measure equal to the share of short-run impacts that are offset in the long run:

$$\frac{\beta_{FE} - \beta_{LD}}{\beta_{LD}} = 1 - \frac{\beta_{LD}}{\beta_{FE}} \tag{4}$$

They then test the null hypothesis that this adaptation measure equals zero. Their simulations of soy and maize outcomes suggest limited adaptation to extreme heat in the U.S.

This insight provides a foundation for using response functions derived from time-series analyses to estimate adaptation. Response functions can be estimated in different physical contexts; for example, Burke and Emerick (2016) measure the response of yields to extreme heat according to short-run variation in the data, and according to short- and long-run variation in the data. Different responses to physically similar events in dissimilar contexts may indicate the presence or absence of adaptation (Schlenker and Roberts, 2009; Auffhammer and Schlenker,

[10] To fully motivate this intuition, see section A.2.1 of Burke and Emerick (2016).

2014). In particular, similar responses may indicate the existence of an adaptation gap, whereby certain adaptations could improve outcomes over time (Carleton and Hsiang, 2016).

This methodology could be expanded by improving the estimation of response functions. These are often calculated in the adaptation literature using single-equation models.[11] However, it may be more appropriate to consider economic outcomes as part of a larger system experiencing structural shocks. An extensive macroeconomic literature estimates how responses to some impulses propagate through an economy.[12] Using tools such as structural vector autoregression could help build more realistic response functions. Then, as noted above, these response functions could be used to identify adaptation gaps.

More generally, the climate adaptation literature has begun combining short-run responses to weather within a larger aggregate framework, in line with that of an integrated assessment model (Auffhammer, 2018; Carleton et al. 2020). This allows researchers to estimate long-run responses to climate change, while allowing for spatial heterogeneity in those responses in the cross-section. This methodology provides a promising framework for analyzing agricultural climate impacts while accounting for long-run adaptive behaviors (Moore and Lobell, 2014). Further, these types of heterogenous responses can then be embedded in aggregate structural models, including spatial general equilibrium models, to capture heterogeneity in certain types of adaptations (Nath, 2020). Thus, the panel approaches discussed above may also be used in conjunction with the structural methods discussed below.

4. Spatial general equilibrium models

The Ricardian approach relies on the assumption that local farmers employ the optimal production adaptations for their particular farm. However, many adaptations are not the result of single agent's optimization of a plot of land. Adaptations such as international trade may be the result of intersecting market forces. Policy makers may want to know if international trade can buffer against the adverse effects of climate change on agricultural outcomes. But reduced-

[11] This includes the response functions estimated in Burke and Emerick (2016) and most of the functions featured in Carleton and Hsiang (2016).
[12] See Ramey (2016) for a comprehensive review, and Stock and Watson (2016) for a precise review of identification techniques.

form assessments of trade may be biased by general equilibrium effects. Therefore, climate economists should consider employing other techniques.

In many contexts, researchers are interested in studying economic interactions across physical space; these approaches can be broadly classified as spatial general equilibrium models. For example, trade models (a type of spatial general equilibrium model) are often used to study how differences in technology drive production specialization and bilateral trade flows. This section reviews how spatial general equilibrium models can be used to study climate change adaptations. This is an extremely broad class of models; thus, to make this review concrete, I focus on how international trade in agricultural goods can be used to adapt to climate change.[13] Therefore, I will first give a brief overview of some of the methodological advantages and disadvantages of trade models that are relevant to understanding climate change adaptation. I then discuss the small but growing literature that uses trade models to estimate how international trade can be employed to adapt to climate change. I conclude this section by discussing spatial general equilibrium more broadly, and identify possible research gaps.

4.1 Overview of trade models

Before describing how trade models are used to understand climate change adaptation, it is useful to review some important elements about trade models more generally. For the purposes of this review, I use the term “trade model” to refer to Ricardian gravity trade models.[14] In a Ricardian model of trade, countries are endowed with different technologies for producing goods. A country has an absolute advantage at producing a good if it is more productive at doing so than other countries. A country has a comparative advantage over other countries in producing a good if it can produce it at a lower relative opportunity cost. In a Ricardian model, countries specialize in producing goods according to their comparative advantage. In a gravity trade model, size and distance have multiplicative impacts on bilateral flows.[15] Thus, a Ricardian

[13] It is worth highlighting terminology here. This section reviews how spatial general equilibrium models can be used to study climate change adaptation. To make this review concrete, I will focus on how a particular category of spatial general equilibrium models (trade models) can be used to understand a particular type of climate change adaptation (international trade). Thus, the methodological tool of trade models should be understood as distinct from international trade as a type of adaptation.

[14] In fact, most of the models discussed here are variants of the Eaton and Kortum (2002) framework. A significant advantage of this model over other types of quantitative general equilibrium models is parsimony; counterfactual analysis can be conducted with only one structural parameter estimate (Adao et al., 2017).

[15] Gravity trade models are meant to capture two key empirical facts often seen in international trade data: (1) trade is proportional to size, and (2) trade is inversely proportional to distance. See Head and Mayer (2014) for a review.

gravity trade model focuses on how comparative advantage and geographical barriers govern trade patterns.

Trade models are designed to capture productivity heterogeneity across space. This makes them well poised to study climate change, as this is expected to have differential impacts on productivity across different regions. For instance, some areas of the world are expected to become better at producing certain crops, whereas other regions are expected to become worse. Crucially, data are available to measure these differences in productivity. Consider the Food and Agriculture Organization's Global Agro-Ecological Zones (GAEZ) database,[16] which contains detailed data on agricultural resources. Of particular interest are the crop-specific potential yield variables.[17] These potential yields are calculated for all crops, not just crops being grown. As such, they can be used to estimate a region's agricultural comparative advantage in a trade model.[18] Given this productivity data, economists can calibrate their trade model.

Once a trade model is estimable, it can be used for counterfactual analysis. Trade models are designed to capture how heterogeneity in productivity leads to particular trade patterns in equilibrium. In general, measures of consumer welfare can be recovered from these models. Assuming a trade model is plausible, an economist can calibrate their model in a world that allows for international trade, and in a world that does not. Because most trade models approximate consumer welfare, it is possible to calculate welfare in a world with and without international trade. The difference between these two arms is called the "gains from trade." This type of counterfactual analysis is a major methodological advantage of trade approaches.

These advantages come at a cost. For parsimony, we generally need strong functional form assumptions that may not be realistic. In addition, counterfactual analysis often describes the steady states, not the transitions. Given the pace at which climate change occurs, transitions may be crucial for understanding economic development. Models are also necessarily limited in scope; they cannot account for all the real-world frictions that might prevent the steady state

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[16] See http://www.fao.org/nr/gaez/en/ for details.
[17] These estimates of crop production potential are constructed using high-resolution measures of crop characteristics, climatic variables (i.e., temperature, precipitation), soil resources, water supply systems and estimated management intensity. Thus, the GAEZ database provides agronomically possible crop yields for 49 different crops across the globe.
[18] This methodology was first employed in Costinot and Donaldson (2012) to evaluate the predictions of the Ricardian model. It has been used to study a number of scenarios; for example, Costinot and Donaldson (2016) estimate the impact of the U.S. railroad system and subsequent market integration on agricultural markets. They do this by applying a Ricardian framework to the U.S. and using productivity estimates from GAEZ.

ever being reached. International trade economists are well acquainted with these trade-offs; some precision is sacrificed to gain an idea about the broader dynamics at play. Even though this type of analysis may never perfectly predict the future, it can, perhaps, provide bounds on impacts or guide thinking about future dynamics. Nevertheless, policy makers and researchers alike are interested in these outcomes, and there is therefore a small but growing literature using trade models to measure agricultural climate change adaptation.

4.2 Application to climate change adaptation

Trade models are adept at summarizing how spatial heterogeneity in crop productivity drives international trade in agricultural goods. However, climate change will have a differential impact on crop productivities across the world, which may shift regional comparative advantage. Given data on how climate change impacts crop productivities, one can estimate subsequent shifts in comparative advantage. This can then be used in a trade model to estimate trading patterns in a world experiencing climate change.

This type of approach was first developed by Costinot et al. (2016). In this paper, the authors use a Ricardian trade model and GAEZ data to estimate how production and trading patterns shift with climate change. Comparative advantage is evaluated using GAEZ potential yield data, which are available for the current climate and estimated under various Intergovernmental Panel on Climate Change scenarios for climate change.[19] These data on comparative advantage can be used in a model of agricultural trade to evaluate various counterfactual scenarios. Specifically, the authors are able to estimate the expected impact of climate change on consumer welfare once trade and production adjustments are taken into account.

The framework provided by Costinot et al. (2016) leaves room for refinement and alternative mechanisms. For example, Nath (2020) employs a similar framework but considers another type of adaptation: sectoral reallocation. Many low-income, agrarian economies are located in hot climates that are particularly susceptible to climate change. However, these areas could adapt to climate change by shifting out of agriculture and into manufacturing or services; food

[19] The GAEZ database is not the only set of data available to study this phenomenon. Cline (2007) estimates the effect of climate change on agricultural productivity, but accounts for certain types of common adaptations within the agricultural sector. This can be useful, as the GAEZ data require researchers to make assumptions about production decisions such as irrigation and input quality that may not be representative of local conditions. For this reason, these are the data used for counterfactual analysis in Nath (2020).

could then be imported from regions that are less impacted. However, this dynamic is complicated by the fact that the agricultural sector in low-income countries is often less productive relative to that of high-income countries, yet maintains a high share of the labor population due to subsistence needs (Lagakos and Waugh, 2013). If climate change drives more workers into agriculture in low-productivity countries due to subsistence requirements, then sectoral reallocation may not occur. Nath builds and estimates a model of international trade and sectoral reallocation to forecast which effect may dominate. His results suggest that climate change may drive more people into subsistence farming, and that current trade policies are not open enough to prevent the subsistence pull toward agriculture. Thus, trade openness may be a key policy for encouraging sectoral reallocation as an adaptation strategy.

Recent advances in trade models can provide further insights for climate researchers. A large class of trade models characterized in Arkolakis et al. (2012) derives the welfare implications of international trade from micro data on the share of expenditure on domestic goods and the consumers' trade elasticity with respect to trade costs. This approach is extended in Dingel et al. (2020) to consider the implications of spatial correlation in agriculture for global welfare inequality. Many of the determinants of economic activity are spatially correlated; if one country is productive at growing a crop, a neighbor with a similar climate is more likely to also be productive at growing the same crop. Dingel et al. empirically validate the prediction that countries gain more from trade in cereals when they have highly productive neighbors, as they are more likely to trade with their neighbors than with distant countries.[20] Overall, the welfare gains from trade appear unequal, being larger for countries that are more productive and smaller for countries that are less productive. This result, while illustrative for understanding current global trade dynamics, is also important for understanding global trade as a type of adaptation to climate change. If changes in cereal productivity due to climate change are spatially correlated, and the predictions of the above model are true, then there may be greater climate-driven welfare losses for low-productivity regions. According to the authors' projections,

[20] It may be worth clarifying that spatial correlation in agricultural productivity implies shared absolute advantage. Dingel et al. (2020) focus on spatial correlation in absolute advantage, which is distinct from spatial correlation in comparative advantage. The latter produces its own interesting implications for the gains from trade: countries that are nearby, but are productive at different things, may have a lot to gain from trade; countries that are far apart, or countries that are nearby and very similar, may have relatively less to gain from trade. The idea that countries with dissimilar technologies have more to gain from trade than those with similar technologies is part of Ricardo's original theory of trade; see Lind and Ramondo (2018) for details.

forecasted welfare losses in a model without spatial correlation in productivities understates the increases in welfare inequality.

In the main, spatial general equilibrium models are useful for predicting the economic dynamics associated with climate change and various macroeconomic types of adaptations.[21] Thus, there is room for a rich crossover between the literature of economic geography and climate change adaptation. And this literature is growing. Desmet and Rossi-Hansberg (2015) build a complex model that, in particular, highlights the role international migration in adapting to climate change. Balboni (2019) builds on the economic geography literature of Redding (2016) and the model from Caliendo et al. (2019) to consider whether infrastructure investments should continue to favor coastal areas. Given the availability of detailed agricultural data, applying these models specifically to agricultural climate change adaptation is particularly promising. Further, although the above summary focuses on trade models, other types of spatial general equilibrium models seem well poised for application to climate change adaptation, including optimal transport networks (Fajgelbaum and Schaal, 2020) and knowledge diffusion models (Buera and Oberfeld, 2020). Overall, broad classes of spatial general equilibrium models are well suited to tackling climate change adaptation questions.

5. Conclusions

In this report, I briefly reviewed the role of panel data analysis and spatial general equilibrium models for studying agricultural climate change adaptation. Recent innovations in the tools used to measure and predict climate change adaptation present promising avenues for future reasarch. Each of these tools on its own cannot perfectly identify climate change adaptation or predict future responses. However, when used as part of a broader toolkit, or perhaps even in conjunction with each another, they can allow us to better measure and predict how our food systems will respond to climate change.

[21] It is worth mentioning that the spatial units studied may not be countries; the unit of analysis may equally be counties within a country or even grid cells within a satellite image. However, all spatial models (including trade models) may be applied in alternative spatial contexts to understand spatial interactions. See, for example, the use of trade models in a regional setting to study intranational pricing (Atkin and Donaldson 2015). See also Costinot and Donaldson (2016); Donaldson and Hornbeck (2016); Donaldson (2018).

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