Approaches to Assessing Climate Change Impacts on Agriculture: An Overview of the Debate

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ABSTRACT

There are three main approaches to assessing the multiple impacts of climate change on agriculture. In this symposium, leading proponents of each approach discuss their methods, uses, and findings. This introductory article provides an overview of these approaches and discusses the main sources of debate in the literature on climate change impacts on agriculture: the weather vs. climate dichotomy, the explanatory variables included in the analysis, the impact measures analyzed, impact projections, and adaptation.

INTRODUCTION

Some of the earliest studies of the impacts of climate change have focused on agriculture (e.g. Adams 1989, National Research Council 1983). In the National Research Council (1983) report, *Changing Climate*, Thomas Schelling (who would later become a Nobel laureate in economics) discussed climate and agriculture (as well as other sectors) and the implications for welfare and policy. Schelling noted the obvious—that agriculture was exposed to weather more than almost any other sector—but that given the state of knowledge at the time, the aggregate impact was uncertain. While there have been many studies and reviews of climate impacts on agriculture since the *Changing Climate* report, Gornall et al. (2010) find that it is still not possible to determine with confidence the aggregate impact of climate change on global-scale agricultural productivity. The Intergovernmental Panel on Climate Change (IPCC 2014) has estimated with only 'medium confidence' that, for the world as whole, the turning point from overall beneficial to negative climate change impacts on crop yields is likely to be associated with a mean global temperature increase above 2°C.

There are three main approaches for investigating the multiple impacts of climate change on agriculture. In this symposium, leading proponents of each of the three approaches discuss the advantages, challenges, and findings associated with panel data analyses (Blanc and Schlenker, 2017), cross-sectional (or Ricardian) analyses (Mendelsohn and Massetti, 2017), and agro-economic analyses (Antle and Stöckle, 2017). This introductory article first provides an overview of these impact assessment methods, and then discusses the main sources of debate in the literature on climate change impacts on agriculture.

IMPACT ASSESSMENT METHODS

The literature includes three broad approaches that are generally aimed at assessing the impact of climate change on agriculture:

(i) **Panel data analyses** use statistical (i.e., regression) techniques to estimate the effect of weather on crop yields or profits by estimating either a production function or a profit function. The empirical estimation of these functions is based on panel data, which include observations of a cross-section of individual units (field, farm, county) over time.

(ii) **Cross-sectional (or Ricardian) analyses** also use statistical techniques to examine the relationship between cross-sectional climate data and measures of agricultural productivity (proxied by land value or total farm revenue). This approach draws on Ricardo's (1817) notion that land values reflect land productivity (which is determined by its intrinsic characteristics).

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(iii) **Agro-economic analyses** use a hybrid structural framework that combines process-based crop models (also called bio-physical models) and livestock simulation models with farm-level economic models to estimate farmers' potential adaptive responses to climate change. Crop simulation models embody a set of parameters related to crop growth processes that reflect the genetic characteristics of the crop type and variety. These models simulate the nonlinear effects of temperature, water, carbon dioxide (CO_2), and nutrients, and their interactions with crop growth and yields, and they can incorporate explicit aspects of management such as altered planting dates, fertilization rates, and irrigation use. The agro-economic framework then integrates the output from the crop model into an economic model that provides information on agricultural production, consumption, and trade. By representing the links between complex systems, such integrated assessments offer the possibility of capturing the interactions between the agricultural and economic sectors and feedback effects.

As the first two approaches use statistical tools to estimate relationships between weather or climate and agricultural output, they are generally favored by economists who prefer to use a method that is based on farmers' actual experience. In contrast, the third approach uses agronomic models, which are generally highly process-based (i.e., biophysical processes are represented by a series of equations) and parameterized on the basis of crop experiments, making it possible to observe and measure relationships between weather conditions and photosynthesis, plant respiration, flowering, seed formation, and ripening.

The main advantage of statistical-based estimates is that they use data from actual farming conditions, thus capturing farmers' economic "optimization" and behavioral responses to risk (which may be quite different from the practices and conditions in controlled agricultural experiments). The main argument for agro-economic analyses is that they are able to incorporate responses to environmental factors that are rarely observed in actual farming conditions. Moreover, these models can separately identify specific environmental impacts on yield (e.g., the impact of CO_2 fertilization on photosynthesis and water use efficiency, the impact of ozone) or the impact of weather that is outside the region in which the crop is normally grown commercially. An agronomic model can also identify adaptation options for farmers, rather than simply observing yield/production outcomes.

SOURCES OF DEBATE IN THE LITERATURE

While the three methods described in the previous section have been widely used in the literature on climate change impact on agriculture, several points of contention remain, including the underlying data; the effects of weather vs climate, CO_2, and prices; the impact measures considered; out-of-sample impact projections; and the role of adaptation.

Underlying Data

The accuracy of results from climate change impact assessments, whether empirical or process-based, is in part determined by the availability of data. Empirical analyses rely on observations of agricultural outputs and explanatory variables for the estimation of the production or profit function. Process-based analyses rely on field experiments for the parameterization and calibration of the model. Agro-economic analyses rely on economic data for the representation of the economic processes.

A significant concern about empirical estimates is the ability to control for all of the relevant variables that may affect the dependent variable, as the omission of some important variables may lead to biased coefficients in the model. However, it is often difficult to account for all possible factors affecting outputs due to a lack of data. Limited data availability for control variables may also lead to omitted variable bias. Panel data allows the use of fixed effects to account for any unobserved effects that do not vary over time to address the potential for misspecification of the model. In addition, thanks to their larger sample size, panel datasets offer more degrees of freedom for statistical analyses. This can be helpful when considering a greater number of explanatory variables, especially weather, which can generally not be reduced to a single variable. Moreover, because some variables are correlated (e.g., ozone pollution and temperature), one may also want to include, or at least test for, monthly means and extremes values, their interaction, and other non-linear effects to disentangle their respective effects. The omission of the representation of a process that influences crop yields can also affect the outcome of bio-physical models. For example, in an inter-comparison of global bio-physical models, Rosenzweig et al. (2014) find that larger crop yield responses to temperature increases are projected by models that consider nitrogen stress explicitly.

The time step (e.g. annual, seasonal, daily) of the set of explanatory variables is also important. Statistical analyses rely on average weather parameters, usually seasonal or annual mean temperature and precipitation, across the spatial unit of interest. As noted by Blanc and Schlenker (2017), these averaged factors can be correlated across seasons. However, by considering seasonal effects, the relationship will capture different parts of the response function, and therefore produce different estimates, even for a unique underlying relationship across seasons. Bio-physical crop models are generally not affected by these types of issues because they consider mechanistically the effect of weather on crop development at a detailed time step (up to hourly for some models). Thus, bio-physical models are better at capturing the effect of extreme weather events than statistical models. However, as pointed out by Antle and Stöckle (2017), the 'close coupling' of bio-physical and economic models has not been accomplished due, in part, to differences in time steps and the associated data.

The spatial scale of the data used for the analysis also has important implications. Global analyses usually rely on spatially averaged data, which can lead to significant attenuation bias[1] (e.g., Schlenker and Lobell 2010). Regarding weather data, most studies rely on data interpolated between weather stations, which can introduce measurement errors (Lobell 2013). For crop yields, country level data are available over long time spans, but may not always be accurately measured, especially in poor countries (Jerven 2013). Satellite-derived data offer an alternative to data aggregation (e.g., Blanc and Strobl 2013), but they do not provide crop-specific information (unless the resolution is high enough to encompass a single crop field).

[1]Attenuation bias is defined as "*bias in an estimator that is always toward zero; thus, the expected value of an estimator with attenuation bias is less in magnitude than the absolute value of the parameter*" (Wooldridge, 2003)

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The use of experimental data by bio-physical models addresses this problem, but the ability of field experiments to represent a region is questionable, and issues arise when these are used to derive regional or global impact estimates. Thus, the availability and variety of spatially and temporally detailed agronomic, climatic and economic data is a fundamental challenge for all modeling approaches to assessing climate impacts on agriculture.

Weather vs Climate

One critical point of contention in the literature is whether the study accounts for weather or climate. Studies based on time series and panel data provide evidence on the effect of unanticipated weather events rather than changes in climate (i.e., the expected average weather conditions). Thus, time series and panel methods largely estimate the biological effect of weather on specific crop cultivars that are currently planted. In contrast, analyses using cross-sectional data over large regions capture the effect of *climate* rather than *weather* (provided that the year considered is representative of normal conditions). When using cross-sectional datasets that include farms that are subject to different climate conditions (to which farmers have adapted over long periods of time), the estimated coefficients capture the *long run* behavioral response of farmers to climate, rather than simply the effect of weather on a specific cultivar or crop (Mendelsohn and Massetti, 2017).

This distinction between weather and climate has implications for the issue of adaptation. Farmers' most critical decisions—what to plant and when—are made at the beginning of a season, *before* the seasonal weather is observed. Because weather changes are unforeseen by farmers, the options for adaptation are limited to some adjustments made after the start of the season (e.g., the amount of fertilizer or pesticide to apply, replanting if the crop is damaged early). These adjustments do not capture all of the potential responses of farmers had they been able to base their decisions on a different expectation of average weather for the season. Moreover, because it is unanticipated, weather can have strong negative effects on agricultural output. This means that other, or additional, analysis is required in order to understand the broader adaptation responses of the farming system to a change in climate. Proponents of the cross-sectional (i.e., Ricardian) approach argue that it captures adaptation among farmers because farms in different climatic zones have had a very long time to adapt to their current climate (Mendelsohn and Massetti, 2017). However, critics have pointed out that a constantly changing climate—where weather is highly variable from year to year—would likely result in a lag in detection and response by farmers (Kelly et al. 2005). To evaluate the effect of such lags and to better represent the challenge of adaptation, Kaiser et al. (1993) used an integrated bio-physical crop model and farm-level economic model to simulate the gradual dynamic adjustment to climate change.

The distinction between weather and climate is also important from an economic perspective. Because the demand for most food products is price-inelastic, a widespread crop failure due to weather events can be associated with a surge in prices and revenues. In contrast, a change in climate will have a more gradual effect on average productivity, with time for farm-level and market adaptation. Analyses that consider a small region in isolation can assume that yield changes there will have no impact on global prices, and thus farm profitability is determined by the yield effect. Of course, the nature of climate change is that it is global, and hence the assumption of no price change would imply a coincidence of yield changes balancing out around the world. Time-series or panel analyses of a production function directly capture the effect of weather. To evaluate the climate effect, one needs to explicitly consider adaptation and long-run market adjustment. Cross-sectional analyses of farm profitability are geared toward implicitly including adaptation, and therefore provide only an estimate of the long-run climate effect; to estimate price effects, they also need to be augmented with market models. Agro-economic models attempt to estimate yield, farm-level adaptation, and market effects; however, the adaptation measures considered can vary from simple to extensive (Antle and Stöckle, 2017).

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CO_2

CO_2 is a major environmental factor associated with climate change because of its impact on crop productivity through its 'fertilization' effect on photosynthesis (directly affecting yield) and water use efficiency (indirectly affecting yield). Experimental results suggest that a 50% increase in CO_2 from preindustrial levels could increase yields of crops like wheat and rice by 9% to 35%, and crop models typically include such an effect (Long et al. 2006, Tubiello et al. 2007). However, while CO_2 may enhance crop yields, it may also cause a deterioration in yield quality (Taub et al. 2008, Högy et al. 2009). Moreover, CO_2 will also favor weed growth, which may hinder and even negate the crop yield gain from elevated CO_2 concentration (Allara et al. 2012, Ziska 2000). These potentially offsetting effects of CO_2 fertilization are generally not included in crop models. Of course, adaptation strategies (pest control, planting different varieties) could be adopted by farmers that might offset some of the adverse effects of CO_2 increases.

In order to estimate the full impact of increases in CO_2 concentration on crop yields, comprehensive studies must account for both the biophysical effect of CO_2 and the adaptation strategies adopted by farmers. On the one hand, statistical analyses can identify the specific impact of CO_2 on crop yields in real farming conditions. However, they are limited because CO_2 does not vary widely over space and time (Sakurai et al. 2014), and its trend over time must be disentangled from crop yield trends due to improvements in technology and management practices (Lobell and Field 2008).[2] On the other hand, although bio-physical models are better suited to represent the bio-physical effect of CO_2 on crop yields, they suffer from uncertainty in model parameterization when large regions are being considered (Challinor and Wheeler 2008, Iizumi et al. 2009).

[2] Mendelsohn and Massetti (2017) acknowledge that cross-sectional analyses do not fully account for CO_2 fertilization.

Prices

As widely traded goods, agricultural products are subject not only to environmental factors, but also to market forces. A weather shock can cause a change in crop productivity, which will affect supply and the relative price of other crops and commodities, which in turn will affect storage and future cropping decisions. It is therefore important to account for price effects when estimating overall climate change impacts. In the literature, price effects are treated differently depending on the method of analysis employed. Thanks to the temporal dimension of the underlying data, panel studies can identify the price effects of either a contemporary (Wright 1928) or past (Schlenker et al. 2013) weather shock. By contrast, cross-sectional analyses can distinguish the effect of exogenous variables from price effects by assuming that prices are constant, as the underlying data are representative of a market equilibrium at a given time. From an experimental design perspective, this assumption is desirable because it avoids the problem of prices biasing the results (Mendelsohn and Massetti, 2017). However, the price assumption underpinning the cross-sectional technique is questionable in developing countries, where markets are not integrated (and market prices are not in equilibrium). Cline (1996) also argues that the hypothesis of constant prices is misleading because it does not account for supply-induced price changes. Moreover, the assumption that prices do not change implies that there is also no change in consumer surplus under the Ricardian approach. With food demand generally price inelastic, but supply price elastic, the overall effect of a price increase would be an overestimate of welfare loss relative to when prices are assumed to be fixed. Of course, the welfare effects for specific consumers and producers, or among exporting and importing countries, needs to consider price changes that are determined in global markets (Reilly 2011, Reilly and Blanc 2010). Because they model behavioral responses to prices and incomes, agro-economic models determine prices *endogenously*, as a function of the climate conditions affecting the supply on the agricultural markets and as a function of demand for agricultural products. This suggests that such integrated assessment models are essential for examining the economy-wide effects of climate change impacts on agriculture.

Measures of Climate Impact

Assessments of climate change impacts on agriculture can be used to examine either physical or economic output. For example, studies using bio-physical crop models and econometric estimates of production functions generally consider only the crop physical response (i.e., crop yields). Ricardian (cross-sectional) analyses and statistical analyses of profit functions consider the economic response (i.e., net revenues or profit). However, projections of the extent of climate change impacts differ between these types of studies, even under similar scenarios of global warming. For instance, for the end of the century in the United States, Deschênes and Greenstone (2012) project small losses in agricultural profit, while Schlenker and Roberts (2009) project large decreases in crop yields. Deschênes and Greenstone (2012) attribute this difference to the outcome considered, contending that profit is more responsive to adaptation than crop yields, even in the short run, and that it provides a more comprehensive indicator of productivity. Thus, the measure of climate change impact must be chosen carefully to ensure that it addresses the question of interest.

Out-of-sample Impact Projections

Another point of contention in the literature concerns projections of future impacts. More specifically, the use of regression estimates to forecast yields is often criticized on the grounds that the estimated coefficients may not be valid for projections because the coefficients represent the impact of *past* climate conditions on agricultural outcomes. If future climate values are not within the range of previously observed values, and if there are non-linearities in the production function that are not apparent in the historical range of climate data, then the relationship between the dependent variable and climate conditions may change. Thus, it is important to assess the ability of econometric models to perform under new conditions using out-of-sample validations. Typically, out-of-sample validation consists of estimating the regression using a subset of the panel dataset and forecasting using the rest of the dataset. Blanc (2017) shows that when using a subset of climate scenarios, statistical emulators are able to replicate both spatial patterns of crop yields and the changes over time that are projected by bio-physical crop models for the scenario that was excluded from

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the panel. Regarding spatial out-of-sample projections, Lobell and Burke (2010) find that statistical models become more appropriate as the spatial scale becomes broader. Bio-physical models are not affected by the issue of temporal out-of-sample forecast because they are calibrated based on control experiments designed to consider extreme conditions and, therefore, offer the option of representing weather threshold effects that may not have been observed in the past. However, projections using such models may not be accurate when making projections over a geographical area different from the experimental sites considered to calibrate the model. To test the out-of-sample prediction capabilities of a hybrid structural model, Antle and Stöckle (2017) used a combined bio-physical and economic-behavioral model to conduct a simulation experiment,[3] and found that the simulated wheat yields and the choice of farming system were consistent with the observations.

The Role of Adaptation

A final area of debate in the literature concerning the three approaches to assessing climate change impacts on agriculture is the role of adaptation. Some studies do not consider the ability of farmers to adapt their production patterns to changing climatic, economic or institutional environments. This omission is important because it may bias impact estimates. For instance, in an extensive meta-analysis of the impact of climate change on yields of maize, wheat, and rice, Challinor et al. (2014) find that adaptation[4] could prevent most yield losses for wheat and rice and that the adaptation strategy having the largest benefit is the change in cultivars. Mendelsohn et al. (1994) refer to this bias as the 'dumb farmer scenario,' arguing that studies that omit adaptation overestimate the negative effects of climate change and underestimate the possible benefits when conditions improve.

[3] A simulation experiment consists of changing one component of the system while holding other components fixed.

[4] Here adaptation measures represent adjustments in planting date, irrigation, cultivar or "other agronomic" changes (e.g., technology change).

In principle, cross-sectional analyses account for adaptation as they assume that farmers at different locations have had time to 'adapt' to their local climate. That is, farmers are supposed to have adjusted crop and livestock mixes in response to local climate in order to maximize profits. More specifically, cross-sectional analyses account for contemporaneous farm level adaptations either implicitly in 'traditional' analyses, with the dependent variables—land values or net revenues—reflecting the costs and benefits associated with each farming practice, including adaptation measures, or explicitly in 'structural' analyses, by measuring the effect of different adaptive measures. In panel data analyses, adaptation can be accounted for explicitly by controlling for specific management strategies, such as fertilizer application (Cuculeanu et al. 1999), or implicitly by modeling adaptation as decreasing sensitivity of maize yields to extreme heat (Schlenker et al. 2013, Butler and Huybers 2013). Bio-physical models make it possible to model specific adaptation strategies such as fertilizer application, changes in planting dates, or changes in irrigation rates. By representing the links between complex systems, integrated agro-economic studies are able to capture interactions and feedback effects, and thus offer the possibility of quantifying climate impacts and assessing technological adaptations.[5]

In part, the difference between methods in their treatment of adaptation stems from the fact that they have different goals. The Ricardian approach has focused on determining the *total* effect of climate change on agriculture, with an eye toward including it in global benefit-cost studies of climate change. The integrated agro-economic modeling approach has focused more on identifying strategies farmers could adopt going forward if the climate changed. The panel approach arose in response to perceived specification shortcomings in the Ricardian approach, and seeks to highlight the potential vulnerability of crops where they are currently grown.

[5] These studies run simulation experiments that use treatment effects that isolate a particular effect from the others.

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CONCLUDING REMARKS

The economic and scientific literature has focused considerable attention on climate change impacts on agriculture due to this sector's inherent vulnerability to weather. The results from the numerous impact assessments have varied greatly across studies, regions, and GHG emission scenario considered. A principal source of difference between results stems from the methodology employed. This symposium presents the three main approaches used to assess climate change impacts on agriculture and discusses the advantages and disadvantages of each method. This introductory article has provided a brief overview of the three approaches and identified specific sources of debate in the literature and how each method addresses the issue at hand. These debates suggest that there are significant challenges to climate change impact assessments, including:

- Global climate change means that growing conditions worldwide are simultaneously changing for all crops. With international trade, and the potential for substitution among crops, the impact on markets would differ for the case in which all crops and regions suffer similar yield declines and the case in which some areas and crops benefit from the change while others are harmed. The evidence from global studies points toward the latter, with poleward regions being more likely to gain from longer growing seasons, and mid and lower latitudes being more likely to suffer from heat or drought. Thus, the challenge for researchers is to provide complete coverage of the globe, because most studies still focus on only a single country or region of a country.
- The economic effect of climate change on a producer (or producing region) depends on how prices change, again requiring global coverage, because partial equilibrium analyses can produce incorrect signs for this effect.
- Regions with subsistence farmers, which generally have poorly integrated markets and limited alternatives for economic activities, may be most vulnerable to the impacts of climate change.

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However, there is currently insufficient economic data to conduct statistical analysis of the most vulnerable regions.

- With global climate change, many environmental factors will likely be changing simultaneously, including CO_2 concentrations, solar radiation, soils, pests, ozone, water resources, coastal inundation, and even infrastructure such as barge transport of inputs to farmers or grains to market.

Unfortunately, even if climate change could be predicted with certainty, we are still far from conclusively determining its effects on agriculture, either globally or for specific farming regions. Estimating accurately the weather or climate effect on crop yield is only the very first step in understanding what it means for farmers in a region, the food supply, and global markets. Thus, further research concerning climate change impacts on the agricultural sector is essential.

References

Adams, R.M. "Global Climate Change and Agriculture: An Economic Perspective." *American Journal of Agricultural Economics* 71, no. 5 (1989): 1272-79.

Allara, M., Kugbei, S., Dusunceli, F., and Gbehounou, G. "Coping with Changes in Cropping Systems: Plant Pests and Seeds." In *Building Resilience for Adaptation to Climate Change in the Agriculture Sector*, edited by A. Meybeck, J. Lankoski, S. Redfern, N. Azzu and V. Gitz. 91-102. Rome, Italy: FAO, 2012.

Antle, John M. and Claudio O. Stöckle. 2017. Climate Impacts on Agriculture: Insights from Agronomic-Economic Analysis. *Review of Environmental Economics and Policy*. [Typesetter – please insert correct final citation/title information; this article is part of the same symposium]

Blanc, E. "Statistical Emulators of Maize, Rice, Soybean and Wheat Yields from Global Gridded Crop Models." *Agricultural and Forest Meteorology* 236 (2017): 145-61.

Blanc, Elodie and Wolfram Schlenker. 2017. Panel Models in Agricultural Impact Assessments. *Review of Environmental Economics and Policy*. [Typesetter – please insert correct final citation/title information; this article is part of the same symposium]

Blanc, É., and Strobl, E. "The Impact of Climate Change on Cropland Productivity: Evidence from Satellite Based Products at the River Basin Scale in Africa." *Climatic Change* 117, no. 4 (2013): 873-90.

Butler, E.E., and Huybers, P. "Adaptation of US Maize to Temperature Variations." *Nature Clim. Change* 3, no. 1 (2013): 68-72.

Challinor, A.J., Watson, J., Lobell, D.B., Howden, S.M., Smith, D.R., and Chhetri, N. "A Meta-Analysis of Crop Yield under Climate Change and Adaptation." *Nature Climate Change* 4, no. 4 (2014): 287-91.

Challinor, A.J., and Wheeler, T.R. "Use of a Crop Model Ensemble to Quantify CO2 Stimulation of Water-Stressed and Well-Watered Crops." *Agricultural and Forest Meteorology* 148 (2008): 1062–77.

Cline, W.R. "The Impact of Global Warming of Agriculture: Comment the Impact of Global Warming of Agriculture: Comment." *The American Economic Review* 86, no. 5 (1996): 1309-11.

Cuculeanu, V., Marica, A., and Simota, C. "Climate Change Impact on Agricultural Crops and Adaptation Options in Romania." *Climate research* (1999): 153–60.

Deschênes, O., and Greenstone, M. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Reply." *The American Economic Review* 102, no. 7 (2012): 3761-73.

Gornall, J., Betts, R., Burke, E., Clark, R., Camp, J., Willett, K., and Wiltshire, A. "Implications of Climate Change for Agricultural Productivity in the Early Twenty-First Century." *Philosophical Transactions of the Royal Society B: Biological Sciences* 365, no. 1554 (2010): 2973-89.

Högy, P., Wieser, H., Köhler, P., Schwadorf, K., Breuer, J., Franzaring, J., Muntifering, R., and Fangmeier, A. "Effects of Elevated CO2 on Grain Yield and Quality of Wheat: Results from a 3-Year Free-Air CO2 Enrichment Experiment." *Plant Biology* 11 (2009): 1-60.

Iizumi, T., Yokozawa, M., and Nishimori, M. "Parameter Estimation and Uncertainty Analysis of a Large-Scale Crop Model for Paddy Rice: Application of a Bayesian Approach." *Agricultural and Forest Meteorology* 149, no. 2 (2009): 333-48.

IPCC. "Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change " IPCC, 2014.

Jerven, M. *Poor Numbers: How We Are Misled by African Development Statistics and What to Do About It*. Ithaca, NY: Cornell University Press, 2013.

Kaiser, H.M., Riha, S.J., Wilkes, D.S., and Sampath, R. "Adaptation to Climate Change at the Farm Level." In *Agricultural Dimensions of Climate Change*, edited by H.M. Kaiser and T.E. Drennen. 136-52. Delray Beach, Florida: St Lucie Press, 1993.

Kelly, D.L., Kolstad, C.D., and Mitchell, G.T. "Adjustment Costs from Environmental Change." *Journal of Environmental Economics and Management* 50, no. 3 (2005): 468-95.

Lobell, D. "Errors in Climate Datasets and Their Effects on Statistical Crop Models." *Agricultural and Forest Meteorology* 170 (2013): 58-66.

Lobell, D.B., and Burke, M.B. "On the Use of Statistical Models to Predict Crop Yield Responses to Climate Change." *Agricultural and Forest Meteorology* 150, no. 11 (2010): 1443-52.

Lobell, D.B., and Field, C.B. "Estimation of the Carbon Dioxide (CO2) Fertilization Effect Using Growth Rate Anomalies of CO2 and Crop Yields since 1961." *Global Change Biology* 14 (2008): 39-45.

Long, S.P., Ainsworth, E.A., Leakey, A.D.B., Nösberger, J., and Ort, D.R. "Food for Thought: Lower-Than-Expected Crop Yield Stimulation with Rising CO2 Concentrations." *Science* 312, no. 5782 (2006-06-30 00:00:00 2006): 1918-21.

Mendelsohn, Robert and Emanuele Massetti. 2017. "Using Cross-Sectional Analysis to Measure the Impact of Climate on Agriculture." *Review of Environmental Economics and Policy*. [Typesetter – please insert correct final citation/title information; this article is part of the same symposium]

Mendelsohn, R., Nordhaus, W.D., and Shaw, D. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *The American Economic Review* 84, no. 4 (1994): 753-71.

National Research Council. *Changing Climate: Report of the Carbon Dioxide Assessment Committee*. Washington, DC: The National Academies Press, 1983.

Reilly, J. "Chapter 13: The Role of Growth and Trade in Agricultural Adaptation to Environmental Change." In *Handbook on Climate Change and Agriculture*, edited by A Dinar and R Mendelsohn. 230-70: Edward Elgar Publishing, 2011.

Reilly, J.M., and Blanc, E. "Chapter 20: Economics of Agricultural Impacts, Adaptation, and Mitigation." In *Handbook of Climate Change and Agroecosystems*, edited by Cynthia Rosenzweig and Daniel Hillel. 403-28: Imperial College Press, 2010.

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T.A.M., Schmid, E., Stehfest, E., Yang, H., and Jones, J.W. "Assessing Agricultural Risks of Climate Change in the 21st Century in a Global Gridded

Crop Model Intercomparison." *Proceedings of the National Academy of Sciences* 111, no. 9 (March 4, 2014 2014): 3268-73.

Sakurai, G., Iizumi, T., Nishimori, M., and Yokozawa, M. "How Much Has the Increase in Atmospheric CO2 Directly Affected Past Soybean Production?". *Scientific Reports* 4 (2014): 4978.

Schlenker, W., and Lobell, D.B. "Robust Negative Impacts of Climate Change on African Agriculture." *Environmental Research Letters* 5 (2010): 1-8.

Schlenker, W., and Roberts, M.J. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences of the United States of America* 106, no. 37 (2009): 15594-98.

Schlenker, W., Roberts, M.J., and Lobell, D.B. "US Maize Adaptability." *Nature Climate Change* 3 (2013): 690-91.

Taub, D.R., Miller, B., and Allen, H. "Effects of Elevated CO2 on the Protein Concentration of Food Crops: A Meta-Analysis." *Global Change Biology* 14 (2008): 565-75.

Tubiello, F.N., Amthor, J.S., Boote, K., Donatelli, M., Easterling, W., Fischer, G., Gifford, R., Howden, M., Reilly, J., and Rosenzweig, C. "Crop Response to Elevated CO2 and World Food Supply: A Comment on 'Food for Thought…'." *European Journal of Agronomy* 26 (2007): 215-23.

Wright, P.G. *The Tariff on Animal and Vegetable Oils*. New York: Macmillan, 1928.

Wooldridge, Jeffrey M. 2003. Introductory Econometrics: A Modern Approach / Edition 2. Mason, OH: Thomson/South-WesternZiska, L.H. "The Impact of Elevated CO2 on Yield Loss from a C3 and C4 Weed in Field-Grown Soybean." *Global Change Biology* 6, no. 8 (2000): 899-905.