Synthesis and Review: an inter-method comparison of climate change impacts on agriculture

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Abstract
The agricultural sector is one of the most sensitive to climate change, with potentially significant implications for food security and welfare. Alternative methodological approaches—such as process models, statistical models and integrated assessment models—have been used to estimate climate impacts on agriculture, not always with consistent results. This focus issue intends to shed light on the sign and order of magnitude of agricultural impacts under 2 °C and higher warming levels. This letter synthesizes the set of articles in the focus issue that have been tasked with providing a systematic assessment of how results from these different methodological approaches compare and why they are different. From this synthesis, we offer thoughts on research priorities going forward to fill key voids in the literature on this important topic.

1. Introduction
Studies have shown that climate impacts on the agricultural sector can have serious distributional consequences, with worrying implications for global food security. For instance, Hertel et al (2010) conclude that less developed countries and low-income social groups appear to be more vulnerable to changes in agriculture prices, and therefore are likely to be significantly affected by changes in climate.

The possible influence of climate change on agriculture has been extensively studied over the last few decades, making agriculture one of the best-known climate impact areas. For instance the Agricultural Model Intercomparison and Improvement Project (AgMIP) is a large-scale international collaborative effort, initiated in 2010, with participation of over 100 institutions, coordinating modeling efforts in an attempt to improve our understanding of climate impacts on agriculture (Rosenzweig et al 2013).

Yet there are still no definitive answers to fundamental questions such as (1) what will agricultural impacts be for different warming levels; (2) what is the role of carbon fertilization; and (3) which cost-effective adaptation measures exist to mitigate potential impacts on specific crops and locations. Resolution on other key issues like the empirical basis behind model projections continues to be elusive, despite vast research efforts so far.

A key reason behind the lack of consensus in the literature is the diversity of methodological approaches. They range from using statistical correlations between climate change variables and agricultural yields (the statistical or empirical approach, e.g. Schlenker and Roberts (2009)) to more detailed models capturing the relevant biophysical links (the process-based or mechanistic crop model approach, e.g. Rosenzweig et al (2014)) to more holistic approaches like those of integrated assessment models (IAMs), e.g. Nelson et al (2014).

Each of the three methodological approaches differ in what is captured and what is not. Statistical approaches, which measure the correlation between weather variables and crop yields, are based on historical observations and therefore capture not only reduced-form biophysical responses to changes in these weather variables but also implicitly farmer adaptation. However, these approaches are ill-equipped to assess the role of specific adaptation options or measure impacts from changes in weather variables outside
of the historical record. Process-based model approaches on the other hand—due to their detailed modelling of biophysical processes—are able to simulate the role of adaptation and capture impacts at finer spatial scales, but require extensive site-specific data for calibration. As a result, these approaches are also often not well-equipped to capture weather extremes since they are calibrated to the range of observational data. Additionally, the effects of carbon fertilization can be incorporated into the biophysical models but are not typically captured in statistical models since CO\textsubscript{2} varies smoothly in space and time (see Lobell and Asseng (2017), for a discussion on how CO\textsubscript{2} can be incorporated in statistical approaches). Neither statistical nor process-based methods capture socio-economic feedbacks on agricultural yields; e.g. changes in prices from climate impacts that can alter input and crop planting decisions, and induce technological innovation. Integrated assessment models, by considering the entire economic system and interlinkages, are designed to capture these feedbacks. However, similar to statistical approaches, IAMs model at coarse temporal and spatial scales and, similar to process-based approaches, are calibrated to one snapshot in time.

The purpose of this focus issue of *Environmental Research Letters* is to provide a better understanding of the magnitude and causes of differences in results from these alternative methodological approaches—statistical models, process models, and IAMs. A comprehensive formal inter-method comparison—similar to the inter-model comparison exercises conducted by the Energy Modeling Forum at Stanford University—where models are harmonized based on a common set of scenarios was not the intent of this focus issue. Rather, in this focus issue we seek, as a first step, to glean insights from comparing across a large set of recent studies that have already been conducted.

This letter reviews the six articles of the focus issue, providing a synthesis of the main findings. The articles were formulated and discussed in a series of three workshops held at Stanford University and the Joint Research Center in Seville, with funding from the US Department of Energy, Office of Science and the Joint Research Center of the European Commission.

The letter is organized into four sections, including this introduction. Section 2 provides an overview of the six articles of the focus issue. Section 3 synthesizes the main findings and section 4 concludes with thoughts on a future research agenda in this area.

### 2. Overview

Table 1 provides an overview of the six papers in this focus issue, including the paper’s main purpose, the inter-method comparison being conducted, crop coverage, and regional scope. These papers fall into two major categories. The first four articles in the table conduct inter-method comparisons of process and statistical models, although they differ in purpose, approaches considered, and regional scope. Lobell and Asseng (2017) compare results on crop sensitivities to weather variables from published process and statistical modeling studies. Moore *et al* (2017a) consider the entire database of yield impact studies from the IPCC 5th Assessment Report, focusing on the role of CO\textsubscript{2} fertilization and adaptation. The other two articles have a US scope. Mistry *et al* (2017) construct emulators from yield impact results of the six globally gridded crop models included in the ISIMIP Fast Track study, and compare the results generated by these emulators with those generated from

| Table 1. Overview of the focus issue articles. |
|-----------------------------------------------|
| Article and Reference | Purpose | Approaches | Crops | Region |
|-----------------------|---------|------------|-------|--------|
| Lobell and Asseng (2017) | Comparison of sensitivities to changes in weather variables | Process and statistical from the literature | Maize, wheat, rice | Global |
| Moore *et al* (2017a) | Comparison of responses from changes in temperature, adaptation and CO\textsubscript{2} fertilization | Process and statistical Meta-analysis of AR5 IPCC (56) studies | Maize, wheat, rice, soybean | World regions |
| Mistry *et al* (2017) | Compare crop model results with historical observations via emulators | 6 process (from ISIMIP-FT) and observations | Maize, wheat, soybean | US (1000 counties) |
| Roberts *et al* (2017) | Evaluate whether combining process and statistical models replicates historical observations better than each alone | 1 process, 1 statistical, 1 combination | Maize | US (corn belt) |
| Calvin and Fisher-Vanden (2017) | Measure the importance of socio-economic impacts on yields | 1 process 1 statistical 2 IAMs | Grains, fruits and vegetables | US |
| Ruane *et al* (2017) | Propose a coupled crop model-IAM framework spanning spatial scales | Crop models (AgMIP), statistical emulators, IAMs | Primarily maize, wheat, rice, soy, plus potato, canola, sugarcane, livestock | Global, with primary regional focus on vulnerable populations and major production areas |
statistical models constructed from historical observations. Roberts et al (2017) combine a statistical model and a process model to see if the combined model performs better than either model separately.

The last two articles examine the role of IAMs, which can capture the socio-economic feedbacks from the impacts of changes in weather variables on crop yields. Calvin and Fisher-Vanden (2017) measure the importance of these feedback effects on crop yields by using results from a process model and a statistical model to incorporate the direct effects of changes in weather variables on crop productivity, and comparing these direct effects with the indirect effects generated by the IAM. Ruane et al (2017) examine the different crop modeling approaches from AgMIP—site-based, network-based, and global approaches—to devise a framework for using these studies to inform IAMs.

In the following section, we highlight the main findings from these six articles.

3. Main findings

The papers comprising this focus issue each take a slightly different approach to comparing yield impact results from process models, statistical models, and IAMs. As a result, they each provide a unique prospective on how and why (or why not) results differ. In this section, we organize our discussion of the six papers around four general questions that we feel encapsulate the main findings.

3.1. Do the different methodological approaches generate significantly different climate responses?

A key finding is that process and statistical models generate similar crop yield sensitivities to changes in climate. More specifically, although individual process model predictions often deviate widely from statistical models predictions, the ensemble average of process models tends to agree well with statistical model predictions. For example, Roberts et al (2017) compare field-level maize yield predictions in the US between a single process model and a statistical model, and find that a +2 °C and +20% precipitation scenario results in modest gains in yields in the process model but strong yield losses in the statistical model. Similarly, Mistry et al (2017) show that individual gridded crop models exhibit very different projected sensitivities to weather-related variables than statistical models (see figures 3 and 5 in Mistry et al (2017)). However, the average of the six gridded models examined in Mistry et al (2017) exhibited fairly close agreement to the statistical model, both in terms of response to high temperatures and climate-related impacts. Likewise, Lobell and Asseng (2017) conclude that up to a 2 °C change in temperature, there is no systematic difference between process and statistical model results, even if individual process model results can differ widely. For higher changes in temperature, there is less consensus because fewer studies have reported results for warming above +2 °C.

Moore et al (2017a) provide a comprehensive comparison of process and statistical model results, based on a meta-analysis of the AR5 IPCC studies, and conclude that on average statistical models are slightly more optimistic (i.e. small yield gains) than process models in low warming scenarios, while in higher warming scenarios statistical models are more pessimistic (generating yield losses). But the uncertainty bounds are large and include zero, indicating no strong differences between methods in the temperature response.

Calvin and Fisher-Vanden (2017) find that the socio-economic feedbacks on yields (captured by the IAMs) are larger (20%—40% higher) than the direct impacts on yields (captured by the statistical- or process-based models). Ruane et al (2017) find that network studies—an open call for crop model participation—provide a better representation of the tails of the distribution, due to their more comprehensive coverage, than site studies.

3.2. What are the key factors influencing the impacts of changes in weather variables on crop yields?

Moore et al (2017a) conclude that CO2 fertilization is a more important source of variability than adaptation or the type of methodological approach. They also find that there is little evidence in the literature for farm-level adaptation to mitigate impacts on yields—many so-called adaptation responses can raise yields under many alternative climate scenarios (including current climate), thus these adaptation measures are not necessarily targeting the mitigation of negative climate impacts on yields.

Under the 8.5 RCP scenario, Calvin and Fisher-Vanden (2017) find that crop yields are higher in IAMs than process-based and statistical crop models due to the inclusion of factors such as technological change, input substitution, and crop switching that mitigate the negative impact of warming on crop yields.

3.3. What is known about the expected impacts under various warming levels (the damage function)?

Moore et al (2017a) find that in a low warming scenario the global response yield, with CO2 fertilization and adaptation, is positive, and becomes negative in the 2 °C to 3 °C range. Without CO2 fertilization impacts are always negative. They also use the GTAP economic model to assess the impacts on welfare and derive an agriculture damage function, with confidence intervals. With CO2 fertilization, the welfare changes are negligible at 1 °C to 2 °C warming, becoming negative at 3 °C. Without CO2 fertilization there are substantial welfare losses at all warming levels.

3.4. Are there ways to combine approaches to generate more accurate results?

Roberts et al (2017) find that for US maize, combining a process model with a statistical model predicts actual
outcomes better than the process model or statistical model alone. The combination harnesses the best features of both approaches—parameters in the process model are estimated by the statistical model based on historical observations while the process model explicitly models the physiological relationships between weather-related factors and crop yields.

Calvin and Fisher-Vanden (2017) find that combining process-based or statistical-based models with IAMs allows the analysis to more accurately predict impacts on crop yields from warming through the incorporation of socio-economics responses—such as changes in technology and management practices, input substitution, and crop switching—that can mitigate the negative impacts on yields.

Ruane et al (2017) suggest that a framework where IAMs are able to draw from a hybrid response system that combines the strengths of site studies with those of gridded crop models would allow for a better connection between bottom-up and top-down analyses, and greatly improve the representation of agricultural impacts in IAMs. That framework also creates an archive of crop model responses which allow integrated assessment models to explore feedback loops and unintended agricultural consequences of policy decisions.

4. Research priorities

A valuable outcome of the inter-method comparison studies included in this focus issue is the identification of important research areas that require much further attention. The key research priorities identified in these studies include:

1. Economics of adaptation: most studies lack a strong representation of adaptation responses. Statistical approaches, to some extent, capture adaptation that is reflected in the historical record, but adaptation in response to large changes that are out of sample are not captured.

2. Better understanding and communication of the CO₂ fertilization effect: the results in Moore et al (2017a), sensitivity analysis in Ruane et al (2017), and prior work discussed in Lobell and Asseng (2017), underscore the importance of understanding and incorporating the CO₂ fertilization effect in these estimates.

3. Expansion of the number of crops: most studies are limited to a narrow set of crops. Even if they represent the bulk of the global calorie intake, they do not cover most of agricultural production in value terms. Economic models usually adopt some heroic assumptions regarding yield changes in these other crops yet without any direct evidence on climate impacts.

4. Pursue hybrid or combination approaches in future studies: a common theme that emerged from most of these studies is that the estimates are more accurate if the different methodological approaches are combined in some way; e.g. Roberts et al (2017), Calvin and Fisher-Vanden (2017), and Ruane et al (2017).

Inter-method comparison studies like those in this focus issue are extremely valuable in improving our understanding of the implications of alternative methodological approaches, with potentially important policy implications.

Similar inter-method comparisons could be conducted on other sectors such as water or energy. Additionally, the studies in this focus issue drew from the vast agricultural impacts literature; however, in most cases these studies were not harmonized on a common set of scenarios, making direct comparisons difficult. In the future, it might be useful to conduct a formal inter-method comparison similar to the inter-model comparison exercises conducted by the Energy Modeling Forum at Stanford.

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