Quantifying the indirect impacts of climate on agriculture: an inter-method comparison

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Abstract
Climate change and increases in CO² concentration affect the productivity of land, with implications for land use, land cover, and agricultural production. Much of the literature on the effect of climate on agriculture has focused on linking projections of changes in climate to process-based or statistical crop models. However, the changes in productivity have broader economic implications that cannot be quantified in crop models alone. How important are these socio-economic feedbacks to a comprehensive assessment of the impacts of climate change on agriculture? In this paper, we attempt to measure the importance of these interaction effects through an inter-method comparison between process models, statistical models, and integrated assessment model (IAMs). We find the impacts on crop yields vary widely between these three modeling approaches. Yield impacts generated by the IAMs are 20%–40% higher than the yield impacts generated by process-based or statistical crop models, with indirect climate effects adjusting yields by between −12% and +15% (e.g. input substitution and crop switching). The remaining effects are due to technological change.

1. Introduction
Climate change and increases in CO² concentration affect the productivity of land, with implications for land use, land cover, and agricultural production. Much of the literature on the effect of climate on agriculture has focused on linking projections of climate change to process-based or statistical crop models. Such models and studies focus on quantifying the direct effect of climate on agricultural yield (production per unit of land). However, changes in crop yields have broader economic implications that cannot be quantified in crop models alone. Quantifying these effects requires a model that captures economic feedbacks, such as an integrated assessment model (IAM) or agro-economic model.

There have been a number of papers, including papers in this special issue, comparing crop yield estimates generated by process-based crop models with crop yield estimates generated by statistical crop models. These models capture the direct effect of climate change on crop yields through changes in temperature and precipitation. However, climate change can affect agriculture indirectly, through price induced changes in input and planting decisions, as well as technological innovation. Assessing the importance of these feedbacks requires the use of a model that captures these feedbacks, e.g. IAMs. IAMs integrate this information with the economic system and other physical systems to capture feedbacks and interactions that cannot be captured by crop models alone.

In this paper, we assess the differences between process-based crop models, statistical crop models, and IAMs in their estimates of climate change impacts on agriculture. This inter-method comparison allows us to address the following research questions. First, how important are these socio-economic feedbacks to a comprehensive assessment of the impacts of climate change on agriculture? Second, in assessing the impacts of climate change on agriculture, what new information can IAMs provide that process-based or statistical crop models cannot?

We demonstrate the role of global integrated assessment models (IAMs) in quantifying these feedback effects, using two different IAMs and two different sources of impacts data. We find that IAMs show fewer
negative effects than process-based and statistical crop models due to the inclusion of factors such as technological change, input substitution, and crop switching. We find the effect of these additional factors to be large, with the additional impact on yields ranging from 20%–40%. Some of these increases are due to the inclusion of technological change, a factor present in simulations both with and without climate change. Other factors (e.g. input substitution and crop switching) are induced by the inclusion of climate effects. The effect of these dynamics range from −12% to +15%.

This paper is organized as follows. Section 2 describes our methodology for implementing agricultural impacts in two IAMs. Section 3 reports the results from two IAMs incorporating two sources of impacts data to illustrate differences in models and methods. Section 4 provides a discussion of the different methods, including pros and cons of each. Section 5 offers concluding remarks.

2. Methodology

To quantify the indirect impacts of climate change on agriculture, we design an experiment that compares agricultural impacts using two different sources of impacts estimates and two different IAMs. In this section, we describe the two integrated assessment models used in the analysis (section 2.1), the process-based and statistical crop model impacts results used as inputs to the IAMs (section 2.2), as well as other coupling decisions (section 2.3).

2.1. Integrated assessment models

IAMs are defined as models that seek to combine knowledge from multiple disciplines in formal integrated representations; inform policy-making, structure knowledge, and prioritize key uncertainties; and advance knowledge of broad system linkages and feedbacks, particularly between socioeconomic and biophysical processes (Parson and Fisher-Vanden 1997). Further, IAMs are designed to capture interactions between multiple systems, e.g. energy, water, land, and climate (Janetos 2009).

We use two different IAMs in our analysis: the Global Change Assessment Model (GCAM) and the IMPLAN model. GCAM is a global IAM, coupling together representations of the economy, energy system, agriculture and land use system, and climate (Clarke et al 2007, Wise et al 2014, http://jgcri.github.io/gcam-doc/). GCAM divides the world into 32 regions in its energy-economy sector and 283 regions in its agriculture and land-use sector. GCAM is a recursive dynamic, market equilibrium model, adjusting prices until supply and demand for each good balance in each time period. Changes in future supply and demand for all goods in the future are the result of socioeconomic changes (e.g. population and income), technological progress, and resource depletion. Technological progress in the agricultural sector in GCAM is based on information from the Food and Agriculture Organization (FAO) (Bruinsma 2009). GCAM is open-source and all code and input files can be downloaded at: www.github.com/jgcri/gcam-core. For this paper, we use GCAM version 4.1 with a slight modification to include climate changes on agricultural yield and carbon density.

The IMPLAN model used in this analysis is a recursive dynamic version of the static computable general equilibrium (CGE) model based on Rausch and Rutherford (2008), which calibrates the model to the state-level social accounting matrices (SAM) for 2007 from IMPLAN. The model comprises 51 producing sectors and five regions of the US (California; Eastern and Southern States; Great Lakes States; Plains States; and Western States (except California)). Economic growth in the IMPLAN model is driven by changes in population and changes in total factor productivity. Population projections were taken from the US Census. Total factor productivity in the non-agricultural sectors is assumed to increase by 1.5% annually. Total factor productivity growth in the agricultural sectors were set to harmonize growth in output in these sectors with GCAM.

GCAM is a partial equilibrium model that takes economic growth as given, while the IMPLAN model is a computable general equilibrium model that captures all sectors of the economy and is able to produce measures of economic growth. GCAM, however, includes a rich representation of land use/land cover change and emissions, while the IMPLAN model does not. Therefore, comparing output from these two IAMs with output from the two crop models, we are able to decompose not only the importance of direct versus indirect effects of climate change on crop yields, but also the effect on both economic activity (via IMPLAN) and land use/land-cover change (via GCAM). More details on both models are provided in the supplementary material (SM) available at stacks.iop.org/ERL/12/115004/mmedia.

2.2. Process-based and statistical crop models

In this study, we compare crop yields from the IAMs to crop yields from a set of process-based and statistical crop models results, to measure the importance of technological change, input substitution, and crop switching when assessing the impacts of climate change on crop yields. As discussed further in the SM, to make this comparable, we use the crop yield results from the process-based and statistical crop model results as inputs to the IAMs.

We use two different sources of impacts data, as each approach has different strengths and weaknesses (see SM3). The process-based crop model estimates are from the Agricultural Model Intercomparison Project
(AgMIP; Rosensweig et al 2014). We use the RCP8.5 simulations with CO₂ fertilization. We aggregate grid-ded crop yield information to the country level for the United States, weighting each grid cell by its 2005 harvested area, for each of the 35 AgMIP simulations (seven crop models forced by five different climate models). We then compute the change in crop yield from 2012. The median of the change across all 35 AgMIP simulations for each of three crops (maize, wheat, soybean) is then used as an input to the IAMs and for comparison with the IAM results.

The statistical crop model estimates are obtained from the American Climate Prospectus (ACP) study (Houser et al 2015). For this study, we use the median estimate of changes in USA crop yields in 2012 from the RCP8.5 with CO₂ fertilization scenario for each of the three crops (maize, wheat, oil seeds). More information is provided in the SM.

2.3. Coupling methodology

In addition to determining which models and which sources of impacts data to use, several other coupling decisions are necessary when designing an impacts study, including the direction, frequency and method of coupling. In this study, we are using ‘one-way’ coupling. That is, we are only including the effect of climate on land and not the influence of changes in land or emissions due to impacts back on climate. Since we are excluding these climate feedbacks, we exchange information for the entire time series at once (i.e. we do not iterate between the IAM and the crop model). As for method of coupling, we are using a soft-coupling approach where data is passed in files to the IAMs. A more detailed description of the various coupling options is included in the SM.

3. Results

In this section, we compare estimated growth in crop yields over time in an RCP 8.5 climate scenario between the ACP statistical crop model results, the AgMIP process-based crop model results, and the two IAMs (GCAM and IMPLAN model). Further, we compare other economic effects, including changes in agricultural production and trade, between the two IAMs. The purpose of this exercise is not to conduct a formal inter-model comparison across all existing methods and models in the literature that generate changes in crop yields, but rather to investigate and highlight potential differences in results when alternative methods are used.

3.1. Crop yields

Figure 1 compares changes in yield over time in the RCP 8.5 scenario across the different methods for two commodities, grains and fruits and vegetables. As shown in the figure, the ACP and AgMIP studies estimate a change in yield for each of these two commodities (2040 changes range from −1% to +1% for grains, 4% to 6% for fruits and vegetables), with three of the four showing an increase, likely due to the inclusion of CO₂ fertilization. However, the growth in yields in both IAM results (red and blue lines) is significantly higher than the growth in yields from the original AgMIP and ACP impacts estimates (black lines). These differences are due to other responses that are captured by the IAMs, but not by the process-based crop models (AgMIP) or statistical crop models (ACP). These effects primarily consist of technological change in the agricultural sector, regional shifts in agricultural production, and input substitution in agricultural production.
Such effects can be significant. In the case of AgMIP, for instance, these factors increase the growth in grain yields in 2040 by 20% in GCAM and 40% in IMPLAN.

While these factors are included in the IAMs’ reference scenario (i.e. scenario absent any changes in climate), the inclusion of climate impacts leads to further adjustments. To measure the relative importance of these factors, we decompose the change in crop yields generated by the two IAMs for grains and vegetables and fruits (figure 2). In this figure, ‘pure climate’ refers to the original AgMIP (top panel) or ACP (bottom panel) yield impacts that are inputs to the IAMs. ‘Total change’ is the change in yields that are generated by the IAMs after the AgMIP or ACP impacts are incorporated into these models. Therefore, the difference between ‘pure climate’ and ‘total change’ represents the total effects on crop yields that can only be captured by models that include economic feedbacks and technological change (e.g. IAMs like GCAM and the IMPLAN model).

However, ‘total change’ also captures underlying changes in yields unrelated to climate. To decompose this, we include two additional yield curves in figure 2. ‘Reference change’ refers to the change in yields in the reference case of each of the IAMs before the AgMIP or ACP agricultural yield impacts are incorporated, which represents changes in yield occurring over time unrelated to climate change impacts. The ‘substitution effect’ is the remaining difference between the AgMIP/ACP impacts and the GCAM/IMPLAN model results.5 This ‘substitution effect’ captures economic adjustments to the impacts on crop yields in response to changes in climate, e.g. through input substitution or technological change. In each case, the difference between the reference case (reflected in the ‘reference change’ curve) and the total impacts case (reflected in the ‘total change’ curve) is much larger (i.e. more negative or more positive) than the original impacts (reflected in the ‘pure climate’ curve), which suggests that these indirect effects (reflected in the ‘substitution effect’ curve) are more significant than the direct pure climate effects. Specifically, the direct climate effect ranges from −1% to +6%, while the indirect climate effect (the ‘substitution effect’ in figure 2) ranges from −12% to +15%.

In addition to input substitution and technological change, crop switching within the ‘grains’ sector contributes significantly to the substitution effect in GCAM. For GCAM, corn and wheat are modeled as separate crops, which were combined as ‘grains’ during post-processing in order to compare with the IMPLAN model, which models corn and wheat together as one ‘grains’ sector. The two crops individually have opposing yield effects in both the ACP and AgMIP scenarios; these differences lead to shifts in production from corn to wheat in GCAM (see section 3.2 and SM).

### 3.2. Agriculture production

Crop switching occurs in both IMPLAN and GCAM in response to changes in crop yields (figure 3). That is, IAMs adjust to climate impacts not only by changing the total amount of production, but by switching crops as well. In the GCAM results (top of figure 3), although the difference from the reference case is small, we see a slight movement toward fodder herb and away from grains and sugar crops in both the AgMIP and ACP cases. As noted above, within the grains category, however, we see a large shift away from corn toward

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5 We define ‘substitution effect’ as ‘total change’ minus ‘reference change’ minus ‘pure climate.’ The ‘substitution effect,’ therefore, eliminates underlying trends unrelated to climate impacts that are captured in the reference case and the direct effects of climate impacts on yield captured in the ‘pure climate’ results.
wheat (figure SM.1), as the yield for corn declines and the yield for wheat increases (figure SM.2). This substitution, between corn and wheat, accounts for nearly all of the substitution effect in GCAM grains, as indicated in figure SM.2. In the IMPLAN results (bottom of figure 3), there is a shift toward oil crops and away from fruits and vegetables and other crops when using AgMIP climate impacts, and a shift toward fiber crops and fruits and vegetables and away from oil crops and other crops in the ACP scenario.

3.3. Trade
Trade in agricultural products will also be affected by changes in crop yields. Figure 4 shows the effect of impacts on crop yields on net exports for grains and fruits and vegetables. In the results from both models, the impacts on net exports are much larger in the ACP case. The average impact on grains yields in the ACP study is negative, so when these effects are included, net exports are less than in the reference case. In the AgMIP case, the yield effects on grains are positive. In IMPLAN, this results in higher net exports than the reference case in 2040. However, the same is not true for GCAM. In GCAM, the negative impact on corn yields in 2040 outweighs the positive impact on wheat yields, resulting in an increase in net exports of wheat and a decline in net exports of corn (figure SM.3). The net result is a decline in net exports of grains. This underscores the importance of sectoral disaggregation. GCAM has much finer sectoral resolution for crops than IMPLAN, and therefore is able to model these crops separately which leads to different results than when the two crops are part of a composite crop—i.e. ‘grains.’ In the case of fruits and vegetables, AgMIP and ACP both estimate a positive impact on yields, so exports will be higher (or less negative) than the reference case. We see this to be the case in both the GCAM and IMPLAN results. In general, we find that increases (decreases) in yields lead to increases (decreases) in net exports (see figure SM.5).
3.4. Economic effects
Changes in yield, production, and net exports have implications for the economy, leading to changes in both prices and GDP. In general, increases (decreases) in yield will lead to lower (higher) prices and higher (lower) GDP. However, given the limited climate signal in 2040 in both the ACP and AgMIP results, we see very little effect on economic variables in this study. For example, corn prices in GCAM are less than 1% higher in the AgMIP case and 2% higher in the ACP case than in the reference.

3.5. Sub-national effects
Lastly, the spatial detail in IAMs allows us to examine the regional effects of agricultural impacts on production. Figure 5 provides maps of the regional effects for GCAM (top of figure 5) and IMPLAN (bottom of figure 5). In the results of both models, we find that the East Coast is more negatively affected by the decline in grains yields from the ACP estimates. When applying the AgMIP yield estimates, results from the IMPLAN model suggest a more positive effect on production in the East Coast whereas GCAM shows a more negative impact on the East Coast production. Again, this is due to the ability of GCAM to separate corn from wheat, which have opposite yield impacts (see figure SM.4).

4. Discussion
In this paper, we compare three different methods (process-based crop models, statistical crop models, and IAMs) used to estimate climate change impacts on crop yields. A few key points emerge from this comparison. First, as expected, technological change, economic responses and interaction effects are potentially large, underscoring the need to include models (e.g. IAMs) that capture these economic feedback effects in assessments of the impacts of climate change on agricultural yields. In theory, statistical models can capture these interactions, to the extent that these effects are reflected in the historical data. However, given the weakness of the climate signal in the historical period, future predicted climate conditions are likely out of sample and statistical estimates based on history likely under-predict the potential response. Additionally, both statistical models and processed-based crop models are essentially static in technology and management practices. IAMs, however, can model future changes in technology and management practices. In theory, these models can capture all future changes in technology and management, but in practice they are limited by data availability. For example, GCAM uses information from FAO to estimate future crop yields absent climate change (Bruinsma 2009) and thus only includes changes considered by the FAO.

Second, a number of issues arise when attempting to incorporate yield impact estimates from a process-based crop model or statistical model into an IAM. Major challenges stem from differences in resolution (spatial, temporal, and crop) and differences in base year data between the crop and statistical models and the IAM. For instance, process-based crop models typically operate on a grid, e.g. the models used in AgMIP used a spatial resolution of $0.5^\circ \times 0.5^\circ$ (Rosenzweig et al 2014). Given data constraints, statistical model estimates are typically done for a specific region and crop. In contrast, IAMs operate on regional scales, with the number of economic regions ranging from $\sim 10$ to $\sim 300$ (see Popp et al 2014). Thus, crop yield information must be aggregated or extrapolated before it can be incorporated into the IAM. Different means of spatial aggregation can result in different estimates of the change in crop yield. For example, (Kyle et al 2014)
Figure 5. Regional changes in grains production for GCAM (top) and IMPLAN (bottom) for the ACP (left) and AgMIP (right) cases. Colors indicate percentage change from the Reference scenario in 2040, with green indicating an increase and red indicating a decrease.

shows differences in yield when grid cells are weighted by land allocation in 2005 versus land allocation in future years.

In terms of temporal resolution, crop models typically run at daily or sub-daily time scales and produce yield effects at annual scales. These yields will reflect the effects of both weather and climate and can be non-monotonic. Statistical models are typically estimated on an annual scale. In contrast, IAMs typically operate on a larger than annual scale. Thus, yield data from crop or statistical models must be temporally averaged prior to use in an IAM. Different methods of temporal averaging may lead to very different results.

Additionally, crop and statistical models often model a small number of representative crops. For example, the number of crops in the AgMIP models ranged from three (maize, rice, wheat) to twelve (Rosensweig et al. 2014). Statistical models have typically focused on one crop or a small number of crops (e.g. maize, rice, soybeans, wheat). IAMs, however, include all crops in the FAO database, but aggregate these to a smaller number of crop categories. The number of crop categories can range from one (e.g. IGSM, iPETS) to 10–20 (e.g. GCAM includes 12). Crop yield data must be mapped, aggregated, and/or disaggregated prior to use by an IAM. Such aggregations can mute results, as shown in the case of grains in section 3.

Next, process-based crop and statistical models and IAMs all estimate yields in both current and future years. In a crop or statistical model, these yields are often simulated and then used as inputs to the IAM. The yields simulated by crop models in the current year, however, may not match the yields generated by the IAM. Thus, using future yields from crop models directly in an IAM may not accurately reflect the change in climate on agriculture present in the crop model. Instead, some method of bias correction is needed. In AgMIP, modelers chose to use a multiplicative index.
of crop yields from crop models (future year divided by base year) to modify the yields in an IAM (Müller and Robertson 2013). Such a method, however, can cause problems if base year yields are very small. Other methods of bias correction exist and could lead to very different results.

Finally, when coupling any two models, there is a potential for double counting processes. For example, some agronomic models include some farm-level adaptation measures (e.g. changing planting and harvesting dates). Researchers must ensure that those adaptations are not also included in the economic model. In this study, neither IAM includes those adaptations.

5. Conclusion

In this paper, we measure the importance of economic feedbacks in assessments of climate change impacts on crop yields. To do this, we compare the direct effects of climate change impacts on yields estimated by process-based and statistical crop models with the results from IAMs that capture important feedbacks and interactions, such as technological change, input substitution, and crop switching. We find that while pure climate effects range from $-1\%$ to $+6\%$ in 2040, the indirect effects of climate range from $-12\%$ to $+15\%$. These indirect effects are thus much larger than the direct effects simulated by crop simulation models or statistical models. Furthermore, factors included in IAMs independent of climate (e.g. technological progress) also substantially increase yields. As a result, the additional impact on yields from all of these factors ranges from $20\%$ to $40\%$.

Although our results demonstrate the important role of IAMs in climate change impact studies, there are challenges that a modeler must face when attempting to couple yield impacts from crop or statistical models into an IAM. Issues related to differences in spatial, temporal, and sectoral resolution; and differences in base year data between crop and statistical models and IAMs must be addressed. These differences can bias results, as shown in our example with aggregating corn and wheat into a grains category.

Lastly, the purpose of this paper was to highlight how widely climate change-induced impacts on crop yields can vary depending on which tool is used (process-based crop models, statistical crop models, and IAMs). This paper does not, however, conduct a formal inter-model comparison of all IAMs and agro-economic models that capture these feedbacks. Therefore, we are unable to fully explore how results may differ across models with different spatial, sectoral, and temporal resolutions and different modeling assumptions such as technological change and substitutability across crops and sectors, to name a few. This would require a coordinated effort among modeling groups to harmonize these assumptions across models in order to conduct such a comparison.

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