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GLOBAL MARKET AND ECONOMIC WELFARE IMPLICATIONS OF CHANGES IN AGRICULTURAL YIELDS DUE TO CLIMATE CHANGE*

KATHERINE CALVIN[†,§], BRYAN K. MIGNONE[‡], HAROON S. KHESHGI[‡], ABIGAIL C. SNYDER[†], PRALIT PATEL[†], MARSHALL WISE[†], LEON E. CLARKE[†] and JAE EDMONDS[†]

[†]*Pacific Northwest National Laboratory – Joint Global Change Research Institute*
College Park, MD, 20740

[‡]*ExxonMobil Research and Engineering Company*
Annandale, New Jersey, 08801
[§]*katherine.calvin@pnnl.gov*

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The economic welfare effects of climate change on global agriculture will be mediated by several complex biophysical and economic processes. For a given emissions scenario, these include: (1) the response of the climate system to anthropogenic forcing, (2) the response of crop yields to climate system and carbon dioxide changes, given baseline improvements in crop yields, (3) the response of agricultural markets to crop yield changes, and (4) the economic welfare implications of such market responses. In this paper, we use information about the first two processes from available climate-crop model comparison studies to analyze implications for the third and fourth processes. Applying the range of crop yield changes in a Global Integrated Assessment Model (GCAM) highlights several important economic relationships. First, we find a consistent relationship between global cropland area and yield change that is approximately orthogonal to the relationship between regional cropland area and yield change. Second, we find that the change in economic welfare, expressed as total surplus change per unit economic output, peaks during the 21st century. Third, we find that, at the global level, changes in yield affect both producer surplus and consumer surplus. Specifically, surplus changes to producers and consumers are always opposite in sign, although which economic actors gain or lose varies with the sign of yield change for any given commodity. Taken together, these results contribute to a growing body of research on climate-induced changes on agriculture by highlighting several economic relationships that are robust to differences in the underlying biophysical responses.

Keywords: Integrated assessment; climate change impacts; agricultural economics.

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§Corresponding author.

1. Introduction

The effects of climate change on world agricultural productivity and markets have been studied for over two decades (Tobey *et al.*, 1992; Rosenzweig and Parry, 1994; Easterling *et al.*, 2007; Porter *et al.*, 2014). Since that time, a variety of approaches have been utilized to further explore potential impacts of climate change on agricultural productivity, including both empirical approaches (e.g., Mendelsohn and Massetti, 2017; Lobell and Burke, 2010; Schlenker and Roberts, 2009; Mendelsohn *et al.*, 1994; Roberts *et al.*, 2017) and process model-based approaches (e.g., Rosenzweig *et al.*, 2014; Roberts *et al.*, 2017; Müller *et al.*, 2018; Bassu *et al.*, 2014). A smaller number of studies have examined the implications of climate-induced yield changes on agricultural markets and economic welfare (Hasegawa *et al.*, 2018; Calvin and Fisher-Vanden, 2017; Nelson *et al.*, 2014; Moore *et al.*, 2017; Stevanovic *et al.*, 2016; Ciscar *et al.*, 2011; Baker *et al.*, 2018).

This paper addresses key gaps in these and other studies focused on economic responses to climate change within the agricultural sector. It demonstrates that several economic relationships can be revealed by making use of the variability in projected biophysical responses to climate change. It does so by exploring economic interactions within a single integrated assessment model, the Global Change Assessment Model (GCAM), across the range of biophysical responses associated with the 35 climate-crop model combinations in the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig *et al.*, 2014).

For a given emissions scenario, there are four key linkages that connect yield changes to changes in economic welfare: (1) between anthropogenic forcing and physical climate responses; (2) between physical climate and carbon dioxide responses and agricultural crop yield responses; (3) between crop yield responses and market outcomes such as cropland area, production, consumption and prices; and (4) between market outcomes and economic welfare changes. Although research is underway to better understand the drivers of differences related to the first two linkages (Rosenzweig *et al.*, 2014; Blanc and Schlenker, 2017; Challinor *et al.*, 2014; Webber *et al.*, 2018; Schleussner *et al.*, 2018; Fronzek *et al.*, 2018), those drivers are not the focus here. Instead, we focus on the third and fourth linkages in this study.[1]

Several prior studies have considered the third and fourth linkages. For example, Nelson *et al.* (2014) consider how climate-induced changes in yield (derived from global gridded crop models) affect economic responses across nine different models in order to understand which outcomes are most and least robust to the choice of economic model. However, production, consumption and price outcomes are not translated into economic welfare changes, limiting the extent to which these results can inform estimates of aggregate climate change impacts. Furthermore, the focus on model inter-comparison limits the extent to which linkages between yield change and economic outcomes within a given model can be explored.

[1]One exception is that we do capture economic adaptation responses that affect global yields, and thus one aspect of the second linkage.

Moore *et al.* (2017) help to fill the gap in economic welfare analysis by estimating the aggregate impacts of climate-induced yield changes. They do so by using available information about climate-yield relationships to statistically estimate response functions that can be included in a CGE model (GTAP) capable of estimating global welfare impacts. However, Moore *et al.* (2017) focused on the distribution across regions rather than the distribution of impact between different market participants (i.e., producers and consumers) and explicitly considered only four crops (maize, wheat, rice and soy) that account for approximately 20% of total agricultural value.

Stevanovic *et al.* (2016) estimate changes in producer and consumer surplus due to climate-induced yield changes, examining both global and regional responses. However, they focus on a subset of climate-crop models within AgMIP and emphasize results that do not include the effects of CO_2 fertilization. Consequently, they do not characterize economic responses across the range of biophysical variability observed within AgMIP.

These studies provide important insights about economic responses to climate change in the agricultural sector, but important gaps remain. Simply put, no study to date has examined global economic responses, including economic welfare and distributional responses, across all crops and across the range of biophysical variability observed within AgMIP. Our study fills this important gap using GCAM, and in doing so, provides a deeper understanding of the mechanisms driving these economic responses. GCAM is an appropriate model for this study, since it has been used in relevant model comparisons (Nelson *et al.*, 2014; Hasegawa *et al.*, 2018) and explicitly represents key processes in the agricultural sector that drive economic outcomes.

Using GCAM, we show that several robust economic relationships can be revealed by making use of the variability in the underlying biophysical responses of the climate-crop model combinations. First, we show that the response to imposed yield changes follows basic economic theory, resulting in fundamentally different relationships between yield and land (and thus production) at the regional and global levels when global trade in agricultural commodities is unrestricted. Second, since global surplus changes are largely driven by changes in price (which follow from changes in yield), we find that producer and consumer surplus changes are always opposite in sign at the global level. That is, when prices rise, producers gain while consumers are harmed, whereas the reverse is true when prices decrease. Third, we show that the change in total surplus in the agricultural sector, when expressed as a share of total economic output, peaks during the 21st century. This occurs because, although net impacts (whether positive or negative) as a share of sectoral value increase in magnitude over time, the sectoral value as a share of total economic output decreases over time.

In the remainder of this paper, we describe the approach in greater detail (Sec. 2), explain the crop yield, market and economic welfare results (Sec. 3) and discuss key insights and implications of these results (Sec. 4).

2. Methods

2.1. *GCAM*

In this study, we use GCAM 5.1 (Calvin *et al.*, 2019), a model that couples energy, agriculture and land-use, water, climate, and the economy to explore global change questions. GCAM subdivides the world into 32 geopolitical regions in the energy system, 235 water basins in the water system, and 384 global land units (GLUs) in the land system. GLUs are formed from the intersection of geopolitical regions and water basins.

GCAM is calibrated to a historical base year of 2010 and projects key variables forward in time through 2100.[2] GCAM is a partial equilibrium model, representing the supply, demand and price for a variety of goods and services in the energy, agriculture (see Sec. S1.1), and water sectors. In this section, we focus on the agriculture-related aspects of GCAM. For a description of other components of GCAM, we refer the reader to (Calvin *et al.*, 2019).

GCAM represents supply and demand for 12 agricultural goods (see Table S1). For these goods, supply (production) depends on the amount of land allocated to a particular commodity, as well as the yield of that land. Land allocation is based on expected profit, as described in Wise *et al.* (2014), with increases in profit leading to increases in land allocation, all else equal. There is a constraint on total land; that is, the sum of each land type cannot exceed the total land area. Additionally, GCAM only includes arable land in each region in the economic competition; other land classes (e.g., tundra, desert, urban) are held constant over time and cannot be reallocated. Land conversion costs are not explicitly included; however, the model implicitly assumes that the cost of each land type increases as that land type expands. Initial yields are derived from a combination of FAO (FAO, 2018), GTAP (Monfreda *et al.*, 2009), MIRCA (Portmann *et al.*, 2010), and HYDE (Klein Goldewijk *et al.*, 2010) data. Yields improve exogenously due to technological change, based on FAO estimates (Bruisma, 2009) and are also affected by climate change, as discussed in the following section.

In addition to exogenous changes in yields, yields may also change endogenously in GCAM 5.1. Price-induced intensification results when higher prices drive increases in yields, which occurs through shifts in management practices. Specifically, GCAM 5.1 includes four different management practices for each crop, including both irrigated and rain-fed technologies, as well as high and low fertilizer application rates. Changes in agricultural commodity price (described below) and cost will lead to different shares of these management practices. The cost of these technologies are not fixed over time, but instead will evolve as the price of fertilizer changes with changes in energy prices (which are also endogenous in GCAM). Shifts toward irrigation and/or high fertilizer application rates will result in higher yields, and vice versa. This version of GCAM does not include explicit constraints on water; instead the model is parameterized to prevent unrealistic shifts towards irrigated agriculture.

[2] A more complete documentation of GCAM is available at: http://jgcri.github.io/gcam-doc/toc.html.

Global yield may also change as regional production shifts in response to regional yield changes. Such production shifts are enabled by global trade of agricultural goods. GCAM 5.1 has relatively flexible trade, with most commodities traded freely on the global market. That is, a commodity produced in one region is treated as a perfect substitute for that same commodity produced in another region, resulting in a single global market price for each commodity. While trade frictions exist in the real world today, it is unclear whether and how these frictions might persist through the end of the 21st century. Yield intensification and regional shifting of production could be considered different types of economic adaptation responses in scenarios that include the effects of climate change.

Demand in GCAM depends on population, income and price, with different price and income elasticities depending on the region and good. GCAM assumes a low price elasticity of demand for food products (-0.08 for crops; -0.25 for meat and dairy) and a zero price elasticity of demand for consumer products (e.g., leather, soap). Therefore, there is effectively a minimum quantity defined by this demand system that must be met globally by GCAM agricultural production. Other demand sectors (biofuels, livestock feed demand) are more elastic. As a result, some crops (e.g., Corn, Oil Crops) have relatively elastic demand, while other crops (e.g., Wheat, Rice, and Roots and Tubers) have relatively inelastic demand. Prior research suggests that the sensitivity of economic welfare outcomes to different assumptions about agricultural price elasticity of demand is relatively small (Stevanovic *et al.*, 2016).

Price in GCAM is calibrated to global producer prices in 2010, which are inferred from prices reported by FAO (2018). Prices evolve in the future in response to changes in supply and demand. Specifically, prices for all commodities in the agriculture, forest and energy sectors are adjusted to ensure that supply is equal to demand in each future model period.

2.2. *Scenarios*

In this paper, we compare crop yield impacts from scenarios that include physical climate and carbon dioxide changes to a scenario that excludes these effects (no-impacts scenario). Both scenarios use population (KC and Lutz, 2017) and GDP (Dellink *et al.*, 2017) assumptions that are based on the Shared Socioeconomic Pathway 2 (SSP2), also referred to as "Middle of the Road" (Fricko *et al.*, 2017).

In the scenarios that include climate change impacts, we modify crop yields in GCAM using output from AgMIP climate-crop model combinations following RCP 8.5 (Riahi *et al.*, 2011). RCP 8.5 has the highest emissions, and thus the greatest forced climate change and CO_2 concentration increase of all the RCPs, allowing us to explore the effects on agriculture over a wide range of future temperatures. AgMIP output from other RCPs would have less rapid changes and smaller overall effects on yields over the century.

The future change in yield for any given crop at a given location depends on: (1) the sign and magnitude of the local change in temperature, (2) the sign and magnitude of the local change in precipitation, (3) the increase in CO_2 concentration, (4) the response of the crop to temperature, precipitation, CO_2 and nitrogen, and (5) management practices (e.g., choices about planting dates, crop variety, irrigation and nutrient application). In this study, we use crop yield outputs from a suite of climate-crop model combinations from the AgMIP global gridded crop model intercomparison study (Rosenzweig *et al.*, 2014) to quantify these effects on crop yield.[3] AgMIP includes seven crop models driven by five climate models, resulting in 35 unique climate-crop model combinations for a given RCP (in this case, RCP 8.5). In all of these cases, we use the versions of these models that include CO_2 fertilization effects. However, the magnitude of the CO_2 fertilization effect varies by crop and by model, and it may also depend on whether other effects (e.g., nitrogen stress) are limiting factors.

In order to capture a wide range of agricultural yield outcomes to study the robustness of key economic relationships, this study does not assign preference to certain models. For example, we include models that represent nitrogen stress explicitly, as well as those that do not do so explicitly. Scenarios that explicitly represent nitrogen stress effectively assume a continuation of current nutrient management practices. Scenarios that do not explicitly represent nitrogen stress could represent a potential future in which such stress is mitigated through enhanced nutrient management practices, potentially as a deliberate adaptation response. Thus, the set of all scenarios (with and without explicit nitrogen stress) spans a wider range of possible future agricultural practices and adaptation responses than a subset of such scenarios. In light of these assumptions, our study includes a wider range of crop model outcomes than Moore *et al.* (2017), which expressed a preference for models that explicitly represent nitrogen stress, and Stevanovic *et al.* (2016), which only used a subset of climate-crop models, with most excluding CO_2 fertilization effects.

AgMIP model output is provided annually at a resolution of $0.5° \times 0.5°$ and provides annual yield information for both irrigated and rain-fed crops for between 3 and 15 crops depending on the crop model. Since GCAM explicitly represents different management practices, yield changes from the AgMIP output are separately applied in GCAM to rain-fed and irrigated crops. To address differences in spatial resolution, we aggregate the gridded yields from AgMIP to GCAM regions, weighting grid cells by their 2005 harvested area, excluding any grid cells with harvested area less than $0.01\,km^2$. To address differences in crops, we map each GCAM commodity to an AgMIP crop type, which varies depending on the specific crop model (see Sec. S1.1).

For all crops, GLUs, and scenarios, we bias correct the AgMIP yields at the GLU level before applying them in GCAM. That is, we calculate the relative changes in yield from 2010 in the AgMIP output. Because GCAM operates using five-year time steps, we take 30-year moving averages of crop yield changes and apply these changes to future yields in GCAM. We discard yield changes for a given crop that are statistical

[3]The crop models participating in AgMIP did not consider the effects of ground-level ozone on crop yields.

outliers, defined as changes of more than 3.2 mean absolute deviations (Davies and Gather, 1993), resetting them to the previous year's yield change.

The resulting scenarios show that there is a large range in yield responses across the AgMIP climate-crop model ensemble both globally (Figs. 1 and S5) and locally (Figs. 4 and S8). The changes in local temperature and precipitation vary across the five climate models. The CO_2 concentration follows a trajectory consistent with RCP 8.5, so the same CO_2 concentration is achieved at the same time but at different temperatures across climate models. The crop sensitivity to CO_2 and management practice vary by crop model and crop; C3 crops (such as wheat) respond more strongly to CO_2 than C4 crops (such as corn) (Ward *et al.*, 1999).

3. Results

3.1. *Crop yield responses*

To arrive at global average yields in Figs. 1 and S5, local yields for each crop are weighted by the land area associated with that crop as projected by GCAM in each future period. As a result, these global average yields include adaptation effects in the form of regional shifts in production, shifts in management practice (irrigation, nutrient

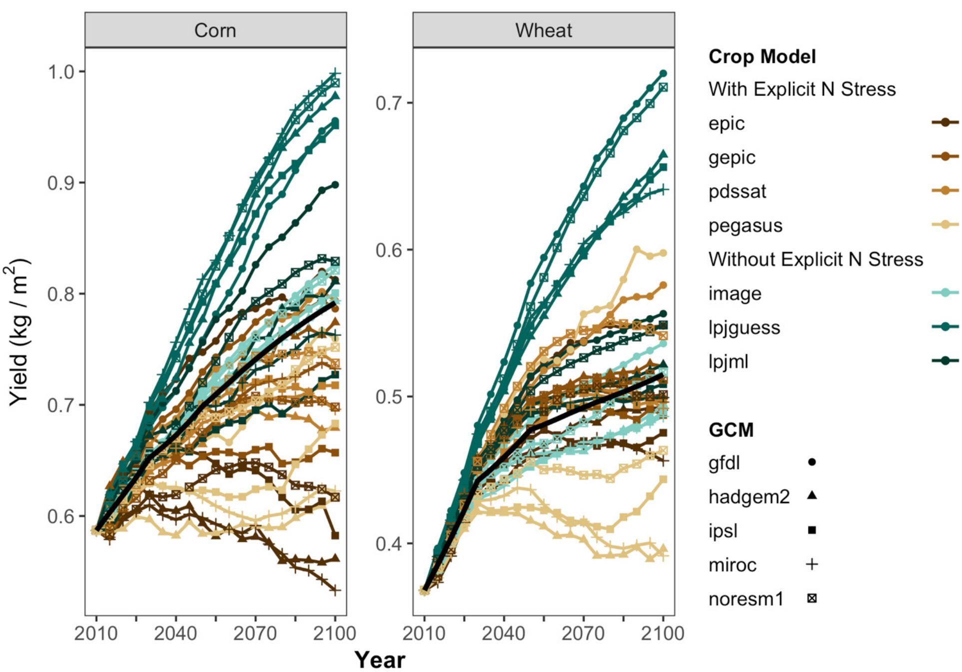


Figure 1. Global average yield for corn (left) and wheat (right), with climate change effects included (green and brown) and without climate change effects included (black). Local yields are weighted by GCAM land area in each period. Brown curves indicate crop models that explicitly represent nitrogen stress.

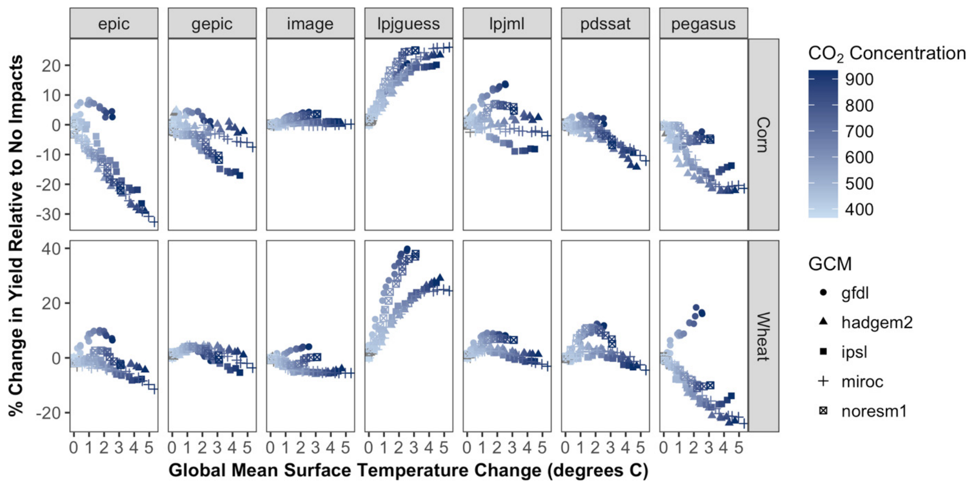


Figure 2. Global average change in yield as a function of global mean temperature change by crop model (columns) for corn (top) and wheat (bottom). Color indicates CO_2 concentration, with darker shading indicating higher concentrations. Global mean surface temperature change is measured with respect to 2010.

application), and therefore yield intensification. Figure S14 shows the global yield when local yields are weighted by GCAM land area for the relevant crop in the initial period, thus omitting the effects of regional shifting over time. The yield changes in these two figures are broadly similar, suggesting that the inclusion of economic adaptation responses does not strongly affect our conclusions about broader agricultural impacts.

Figures 1 and S5 suggest that crop model is a strong determinant of global yield in any given year. Crop models that do not explicitly represent nitrogen stress (green curves in Fig. 1) generally exhibit higher yields under climate change relative to the no-impacts scenario (black curve). Crop models that do explicitly represent nitrogen stress (brown curves) generally exhibit lower yields under climate change relative to the no-impacts scenario (black curve).

When global average yields are plotted versus global mean temperature change (Figs. 2 and S6), the clustering of yield response pathways within a given crop model suggests that yield response is strongly correlated with temperature change for any given crop. Because the same CO_2 concentration is achieved at the same time, but at different temperatures across climate models, some of the divergence in response pathways within a crop model is due to CO_2 fertilization, particularly for C3 crops such as wheat (Fig. 2, bottom row). In addition, the spatial distributions of projected temperature and precipitation differ by climate model, so some of the differences in response pathways within a crop model are also due to these factors.

3.2. *Global and regional yield-land relationships*

Global land-yield relationships follow from a simple theoretical relationship. Global yield, production and land area are linked given that land $= \frac{\text{production}}{\text{yield}}$. If the price elasticity of demand were zero, then global demand and thus global production in a given year would be fixed, and the change in land area would be a function of the change in yield: $\delta_L = \frac{-\delta_Y}{1+\delta_Y}$, where δ_L is the relative change in land area and δ_Y is the relative change in yield (see Sec. S1.3). For crops with a small price elasticity of demand (such as Wheat in GCAM), the model results are consistent with the theoretical approximation (see results for wheat in Fig. 3). For crops with larger price elasticity of demand (such as Corn in GCAM), there is less agreement between model results and the theoretical approximation (see results for corn in Fig. 3). In all cases, however, increases in global average yield result in reductions in global cropland area, while the reverse is true for decreases in global average yield (see also Fig. S7).

The global results in Fig. 3 are not replicated at the regional level. Specifically, the relationship between regional cropland area and yield is approximately orthogonal to the relationship between global cropland area and yield (Figs. 4 and S8). The global land requirement is determined from the global average yield change (higher yields imply less land area needed), but regional increases in yield for a given crop tend to increase the regional land area devoted to growing that crop, as increased profitability leads land owners to switch to that land type. The regional land changes may be positive or negative but must sum to the change in the global land requirement.

Increases in price also result in increases in land area, even absent any regional yield changes. That is, at the regional level, change in land does not always equal zero when the change in yield equals zero. Lower global average yields mean higher prices, and

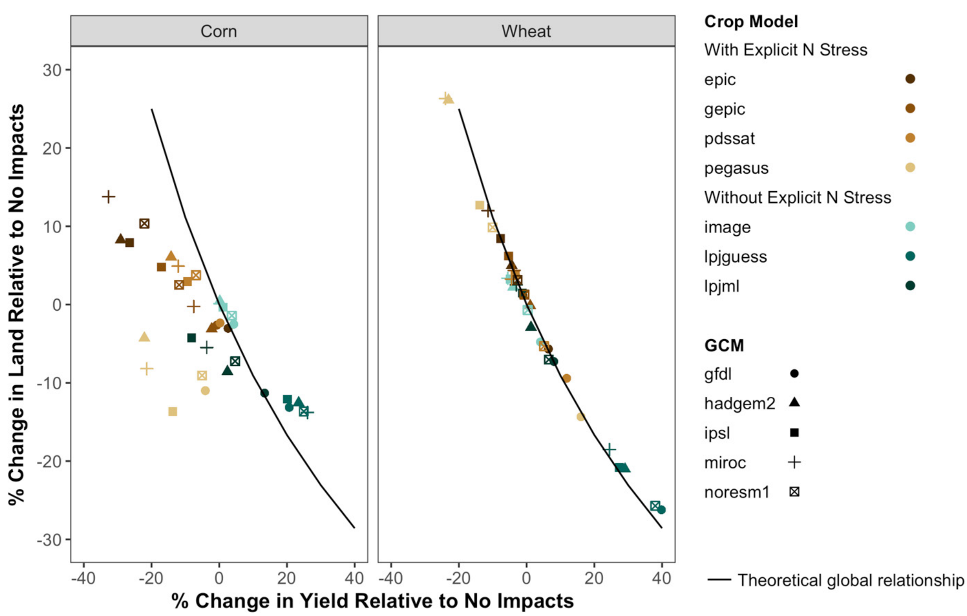
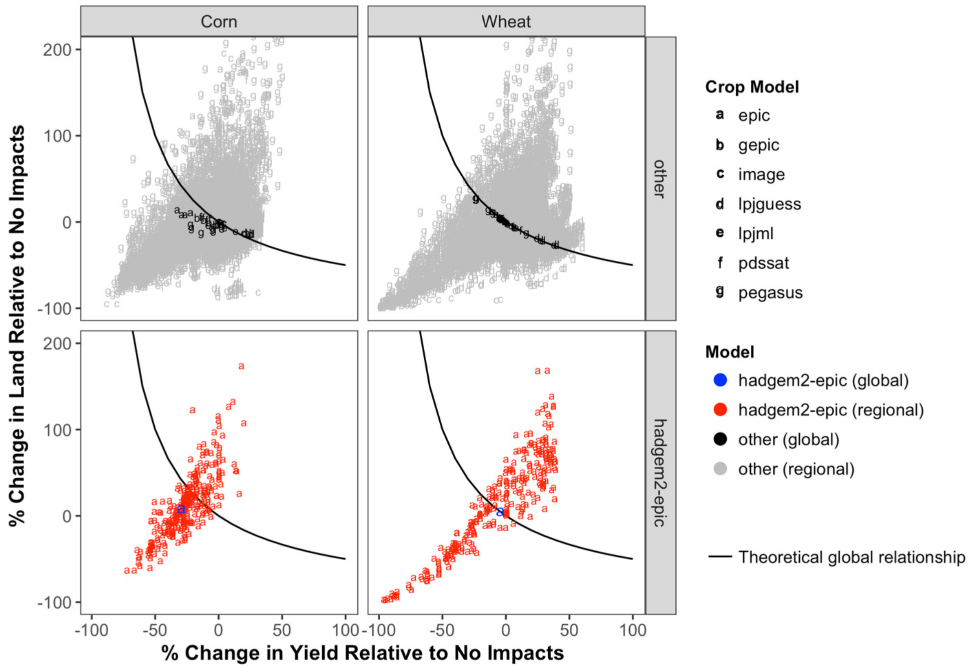


Figure 3. Change in global land in 2100 as a function of the change in global average yield for corn (left) and wheat (right). Brown markers indicate crop models that explicitly represent nitrogen stress. The black curves show the theoretical relationship described in the text.



Notes: Only GLUs with land area greater than 10 km^2 in 2010 in the no-impacts scenario are shown.

Figure 4. Change in global land (blue or black) or regional land (red or gray) in 2100 as a function of the change in yield. The bottom panel (red and blue markers) indicate land and yield for one particular climate-crop model combination (HadGem2-EPIC); each red marker is an individual GLU and the blue marker is the global average. All other climate-crop models are shown in the top panel with black and gray markers. The black curves are identical to the ones in Fig. 3.

thus, more land is allocated at the regional level for any given regional yield change. The reverse is true for higher global average yields.

The approximate orthogonal relationship between land area and yield at the global and regional levels results from the assumption of frictionless global trade in agricultural commodities. At the opposite extreme, were there is no trade among regions, land area changes at the regional level would scale inversely with regional yield, thus mirroring the relationship between global land area and yield. Since trade patterns at the end of the 21st century are deeply uncertain, the results here are meant to provide insight into the forces that will shape the relationship between future yield changes and future land area changes.

3.3. *Economic surplus in global crop markets*

For any given crop, changes in price and changes in production that result from climate-induced changes in yield will lead to changes in revenues, as well as to changes in consumer, producer and total surplus. As discussed above, changes in yield

Table 1. Projected global changes in yield, price, revenue and surplus in 2100 relative to the no-impacts scenario by GCAM commodity. The left entry in each cell is the value from the climate-crop model combination with the smallest (most negative) change in total surplus, and the right entry in each cell is the value from the climate-crop model combination with the largest change in total surplus. Total is a weighted sum of individual commodities, with production used as weights. Fodder crops are excluded from this table and in the total, but the total row captures 85% of global agricultural value in 2100. The contribution of each commodity to total production and agricultural output is shown in Fig. S10.

GCAM commodity	Change in yield (%)	Change in price (%)	Change in revenue (%)	Change in consumer surplus (% of revenue)	Change in producer surplus (% of revenue)	Change in total surplus (% of revenue)
Corn	−21 to 21	51 to −17	9 to −13	−36 to 3	7 to −6	−29 to −2
Fiber Crops	−17 to 57	39 to −26	27 to −19	−33 to 12	11 to −9	−22 to 3
Misc. Crops	−17 to 49	5 to −3	2 to −2	−7 to 4	0 to 0	−7 to 4
Oil Crops	−28 to 54	50 to −28	20 to 3	−31 to 6	10 to −5	−21 to 2
Other Grain	−8 to 25	34 to −21	29 to −18	−27 to 9	10 to −7	−17 to 2
Palm Fruit	−59 to 63	50 to −16	−4 to 14	−50 to 26	7 to −5	−43 to 22
Rice	−30 to 83	72 to −35	61 to −32	−74 to 31	24 to −14	−50 to 17
Roots and Tubers	−20 to 51	11 to −6	9 to −7	−12 to 5	3 to −1	−9 to 4
Sugar Crops	−45 to 3	74 to −7	55 to 0	−68 to 7	21 to −2	−46 to 5
Wheat	−24 to 40	40 to −24	34 to −22	−39 to 19	13 to −9	−25 to 10
Total	−21 to 37	30 to −14	15 to −8	−25 to 8	6 to −3	−18 to 5

can vary considerably across different models and crops. For the agricultural sector as a whole, the production-weighted average yield change in 2100 varies between −21% and +37% for the models that exhibit the smallest (most negative) and largest changes in total surplus, respectively (see Total row in Table 1).

Imposed changes in yield for any given crop lead to changes in price for that crop. Relative changes in price do not necessarily scale directly with relative (negative) changes in yield, because there is a floor on the production cost of any given crop. Visually, this cost can be approximated by the y-intercept of the supply curve in Fig. S2. In the presence of such minimum costs, the relative change in price for a relative change in yield is not constant, but is itself yield-dependent.[4] As a result, the production-weighted average change in price for all crops across the end member models in 2100 is −14% to +30% (see Total row in Table 1).

Changes in price, combined with changes in production, lead to changes in revenue. When demand is inelastic, then the relative change in revenue equals the relative

[4]Specifically, negative changes in yield produce disproportionately larger increases in price, and positive changes in yield produce disproportionately smaller decreases in price. To see this, suppose a supply curve for a given crop is: $P = f + Q/y$, where P is price, Q is production, y is yield and f is a fixed minimum production cost. Then the relative change in price with respect to the relative change in yield is: $dP/dy{*}y/P = -Q/Py$. When yield is smaller, the relative change in price is larger and vice versa.

change in price. This is approximately true for several crops (e.g., see wheat in Table 1). When demand is more elastic, then changes in revenue are smaller than relative changes in price, because demand declines when prices rise, and vice versa (e.g., see corn in Table 1). As a result, the production-weighted average change in revenue for all crops across the end member models in 2100 is -8% to $+15\%$, considerably smaller than the range in the average change in price.

When demand is inelastic and minimum production costs are small, then surplus changes are straightforward to estimate (see example in Sec. S1.2). Under these conditions, the change in consumer surplus is equal to the change in revenue, and the change in producer surplus, which is opposite in sign, is equal in magnitude to half the change in consumer surplus (or revenue). The change in total surplus is then equal in magnitude to the change in producer surplus but opposite in sign (e.g., see wheat in Table 1).

When demand is elastic or when minimum production costs are significant, the effect on surplus is more complex. For example, significant minimum production costs reduce producer surplus (in Fig. S1, such costs decrease the area between the market clearing price and the supply curve for a given crop). Changes in consumer surplus are not similarly impacted by minimum production costs, but consumer surplus is affected by price elasticity of demand. As a result of these factors, the production-weighted average change in producer surplus (-3% to 6%) is less than half the change in consumer surplus (-25% to 8%). Changes in total surplus for the sector (-18% to 5%) are therefore dominated by changes in consumer surplus.[5]

Figure 5 shows consumer surplus, producer surplus and total surplus changes for corn and wheat across the range of climate-crop models in 2100. Under the simplest conditions, relative changes in total surplus are approximately half the relative changes in price. Further, changes in producer surplus are approximately half as large as consumer surplus (and opposite in sign) as anticipated from the simple example. For corn, and the crops considered in Fig. S9, the relationships are more complex, consistent with the discussion above. However, the consistent difference in sign between producer and consumer surplus changes at the global level indicates that any changes in yield will likely have significant distributional consequences that are not fully captured by metrics such as total surplus change. In addition, changes at the regional level are likely to be more complex, because changes in production may be more significant than changes in price, leading to situations in which producer and consumer surplus move in the same direction.

[5]Since consumer surplus is unbounded, total surplus is also unbounded. Therefore, relative changes are undefined for these surplus terms. As an alternative, changes in surplus are normalized by revenue to calculate relative changes. Using this definition, the relative change in consumer surplus scales with the relative price change in the simple example provided in Sec. S1. That is, $d(CS) = Q^*dP$, so $d(CS)/R = Q^*dP/(Q^*P) = dP/P$. Relative changes in TS and PS are directly related to changes in CS if they are all normalized by the same factor (R).

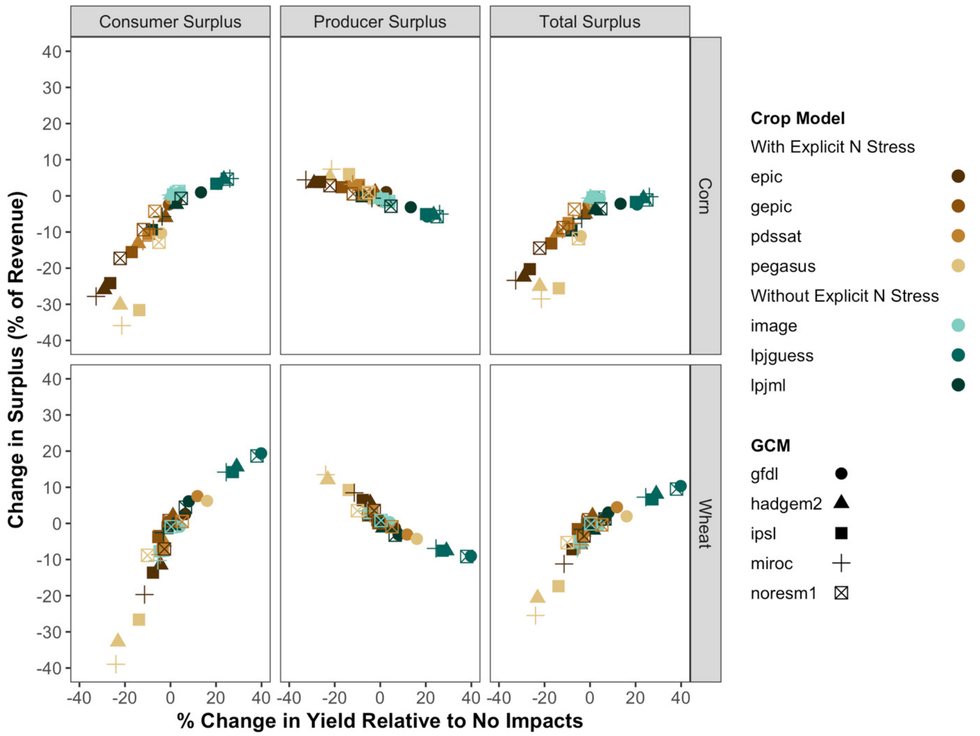


Figure 5. Change in global consumer (left), producer (middle) and total (right) surplus in 2100 as a function of change in yield for corn (top) and wheat (bottom). Brown markers indicate crop models that explicitly represent nitrogen stress.

3.4. *Contextualizing economic responses*

To be considered alongside other monetized climate change impacts, changes in total surplus can be expressed as a percent of global income (GDP) and can also be shown as a function of realized temperature change (see Fig. 6). Changes in total surplus relative to income can be expressed as the product of two terms: (Change in total surplus/total revenue)*(total revenue/GDP). The first term has been discussed above (see Table 1 and Fig. 5) and is expressed as a function of temperature in Fig. 6 (left panel). The second term is shown in Fig. S12. Since the value of the agricultural sector as a share of global economic output (the second term) declines approximately exponentially over time in SSP2, the change in surplus expressed relative to global income also eventually declines in magnitude over time, as observed in Fig. 6 (right panel).[6] For example, the total surplus change in the climate-crop model with the highest peak value (GFDL-LPJGUESS; green circles) is 0.07% at the peak, but 0.04% by the end of the century. The total surplus change in the climate-crop model with the

[6]The change in surplus as a share of income depends on the agricultural share of economic output, which varies with the choice of SSP. In 2100, the agricultural share of output varies between 0.3 and 3.6% across the SSPs, with the agriculture share of output in SSP2 (used here) approximately equal to 0.9% (Calvin *et al.*, 2017).

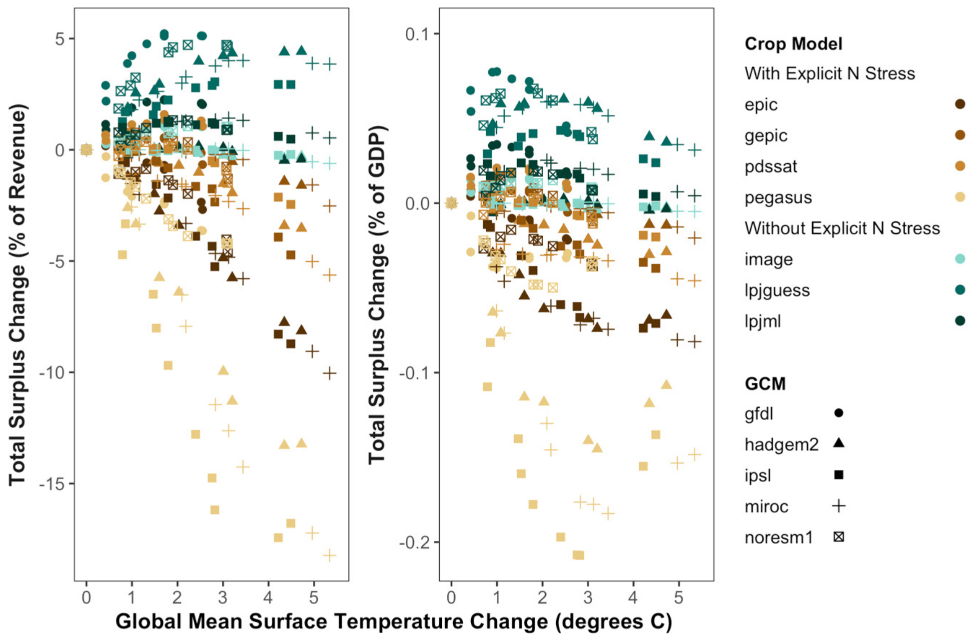


Figure 6. Change in total surplus as a percent of revenue (left) and as a percent of GDP (right) as a function of change in global mean temperature for all crops. Brown markers indicate crop models that explicitly represent nitrogen stress. GDP and agricultural output per GDP are shown in Figs. S11 and S12, respectively. Fodder crops are excluded from total surplus. Global mean surface temperature change is measured with respect to 2010.

lowest (most negative) peak value (IPSL-PEGASUS) is −0.21% at the peak but −0.13% by the end of the century.

The magnitude of the total surplus change as a share of global income can thus be traced from the original yield changes using the relationships discussed above. For the cases with the minimum and maximum changes in total surplus described in Table 1, the change in total surplus varies between −18% to +5%. In 2100, the value of the agricultural sector is about 1% of total economic output under SSP2, leading to total surplus changes between approximately −0.2% and +0.1% of total economic output, as observed in Fig. 6. Earlier in the century, agriculture is a larger share of total output, but relative yield changes are smaller since temperature changes are smaller (Fig. S13), so the product of these terms is similar to that in 2100.

4. Discussion and Conclusions

By focusing on the linkages between biophysical responses and market and economic welfare outcomes using a well-known integrated assessment model, this study helps to fill four important gaps. First, it considers a broad range of climate-crop model combinations as inputs to understand how climate and biophysical differences contribute to differences in economic responses. Second, it focuses on key drivers within a single model (GCAM) to develop a deeper understanding of the mechanisms driving projected economic responses. Third, it considers distributional consequences within the agricultural sector. Fourth, it provides insights about the scale of net agricultural impacts that provide context for assessing these impacts relative to other sectors.

One important insight from this work is that several economic relationships can be revealed by making use of the variability in yield responses from the AgMIP climate-crop model combinations. These include the relationships between cropland area and yield (with the regional and global relationships approximately orthogonal to one another when global trade is unrestricted), the relationship between global consumer and producer surplus changes (consumer surplus changes are larger than but opposite in sign to producer surplus changes), and the relationship between total surplus change and temperature (which peaks during the 21st century). These insights help to place agricultural impacts in the context of potential climate change impacts from other sectors and provide additional perspective on the distributional consequences within the agricultural sector.

It is important to note that several effects have not been addressed in this study. First, this study does not consider distributional outcomes within and across regions. Second, this study does not consider the potential effects of short-term (intra-annual or inter-annual) climate variability or changes in such variability on the agricultural sector. Third, this study does not consider the potential impact of climate mitigation on agricultural commodity prices, which some studies have suggested could be larger than the direct impacts of climate change, depending on the stringency of mitigation (Hasegawa *et al.*, 2018). Fourth, this study does not consider potential non-market impacts of climate change, such as broader social consequences that might indirectly follow from changes in agricultural yields, prices or revenues in certain regions.

Fundamentally, both the sign and magnitude of future yield changes will determine the sign and magnitude of key economic outcomes, including overall economic welfare changes, as well as distributional outcomes. These climate-induced changes in yields are likely to occur against a backdrop of exogenous technical change that will increase yields, all else equal. Our results support prior conclusions that differences in crop responses to CO_2 fertilization and future nitrogen stress contribute to the overall variability observed between different climate-crop model combinations, and thus in the economic responses. This implies that changes in crop yields will depend in part on whether producers have adequate market signals to respond to nitrogen stress and how they choose to respond to those signals in the future. Although the variability in biophysical responses is useful for revealing certain economic relationships, this study also suggests that the range in economic responses cannot be narrowed without first narrowing the range in biophysical responses.

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