Food Policy 95 (2020) 101954

Contents lists available at ScienceDirect

Food Policy

journal homepage: www.elsevier.com/locate/foodpol

Viewpoint

Viewpoint: Climate impacts on agriculture: Searching for keys under the streetlight☆

Thomas W. Hertel[a,b,*], Cicero Z. de Lima[a]

[a] Center for Global Trade Analysis, Purdue University, West Lafayette, IN 47907, United States
[b] Purdue Climate Change Research Center, United States

ARTICLE INFO

Keywords:
Climate impacts
Agriculture
Heat stress
Nutrition
Productivity

JEL code:
Q54

ABSTRACT

This paper provides a critical assessment of the literature estimating the consequences of climate impacts in agriculture and the food system. This literature focuses overwhelmingly on the impact of elevated CO2 concentrations in the atmosphere, higher temperatures and changing precipitation on staple crop yields. While critically important for food security, we argue that researchers have gravitated to measuring impacts 'under the streetlight' where data and models are plentiful. We argue that prior work has largely neglected the vast majority of potential economic impacts of climate change on agriculture. A broader view must extend the impacts analysis to inputs beyond land, including the consequences of climate change for labor productivity, as well as for purchased intermediate inputs. Largely overlooked is the impact of climate change on the rate of total factor productivity growth and the potential for more rapid depreciation of the underlying knowledge capital underpinning this key driver of agricultural output growth. This broader view must also focus more attention on non-staple crops, which, while less important from a caloric point of view, are critically important in redressing current micronutrient deficiencies in many diets around the world. The paper closes with numerical simulations that demonstrate the extent to which limited input and output coverage of climate impacts can lead to considerable underestimation of the consequences for food security and economic welfare. Of particular significance is the finding that humans in the humid tropics are likely more vulnerable to heat stress than are many of the well-adapted crops, such as rice. By omitting the impact of heat stress on humans, most studies of climate impacts greatly understate the welfare losses in the world's poorest economies.

1. Introduction and knowledge gaps

All empirical research is opportunistic – at least to some degree. We tend to focus on topics for which data and methods are readily available. There is a widely employed metaphor used to describe research that focuses on accessible topics to the exclusion of other important avenues of research, suggesting that *you are searching for your car keys under the streetlight*. This relates to the apocryphal tale of a drunk who is confronted by a police officer while searching for his keys under a well-

☆ The authors acknowledge valuable comments on an earlier draft by Christopher Barrett and Keith Fuglie as well as two anonymous reviewers. Hertel acknowledges additional support from USDA-AFRI grant #2019-67023-29679: "Economic Foundations of Long Run Agricultural Sustainability" and NSF-INFEWS grant #1855937: "Identifying Sustainability Solutions through Global-Local-Global Analysis of a Coupled Water-Agriculture-Bioenergy System".
* Corresponding author at: Center for Global Trade Analysis, Purdue University, West Lafayette, IN 47907, United States.
E-mail address: hertel@purdue.edu (T.W. Hertel).

https://doi.org/10.1016/j.foodpol.2020.101954
Received 6 April 2020; Received in revised form 20 July 2020; Accepted 22 July 2020
Available online 11 August 2020
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lit section of sidewalk.

"I'm searching for my keys"

When the man admits that he lost the keys in the park, the officer asks: 'So why aren't you looking over there?' At this point the drunk responds: 'this is where the light is'! While admittedly a caricature, this paper will argue that most of those researchers currently analyzing the impacts of climate change on agriculture (present authors included!) have fallen prey at some point to searching for such impacts 'under the streetlight' where well established data and methods already exist. Meanwhile we have abstracted from potentially larger and more significant, but harder to quantify, impacts elsewhere in the agricultural sector.

The field of research where climate impact assessments have been most fully developed pertains to the impacts of climate change on staple crops such as maize and wheat. It was natural for crop modelers who had spent their career developing tools to guide management decisions in wealthy, industrialized economies, typically in temperate climates, to turn to these models when first asked to assess climate change challenges at global scale. Indeed, when White et al. (2011) reviewed 221 studies of climate impacts on crops, they found that only a handful studies considered the effects of elevated CO2 on canopy temperature, and similarly few studies considered direct heat effects on key crop developments. While these features were not central to management decisions in the temperate environments where most of these crop models were developed, they are critically important under future climate change – particularly in the tropics where elevated temperatures already pose a challenge. This is problematic given the high degree of exposure and vulnerability of the world's low-income populations currently living in the tropics. Fortunately, through the efforts of AgMIP: the Agricultural Modeling Intercomparision Project (Rosenzweig et al. 2013), there have been significant efforts to extend the validity of these crop models to developing countries.

The vast majority of these climate impact analyses have focused on a few staple crops, including maize, rice, soybeans and wheat. Yet staple grains and oilseeds account for only about one-quarter of global agricultural output, measured in value terms. And, while these staple food products are the predominant sources of caloric intake in the world (that is why they are called staples), today's malnutrition challenges are much broader (Gómez et al. 2013), and the coverage of climate impacts on crops providing critical micro-nutrients is relatively weak. Furthermore, there is now evidence that climate change itself may reduce the micro-nutrient intensity of many of the world's crops (Myers et al. 2014). In addition, analysis of climate impacts on livestock production – a key source of protein globally – has been largely neglected (McCarl and Hertel 2018). In this paper, we will highlight just how important are these gaps in our knowledge of climate impacts, calling for researchers to start looking for key impacts beyond the bright streetlights.

A decomposition of sources of output growth over the past half-century complied by USDA/ERS (2019) highlights a critical dimension of food production which has received relatively little attention from climate scientists, namely total factor productivity (TFP) growth. TFP growth is typically attributed to one of two sources: economic reforms that result in improved efficiency in the farm sector, and the accumulation of knowledge capital which, in turn, is translated into innovations that improve farm productivity (Alston et al. 2010). Economic reforms typically generate one-off gains, and so it is hardly surprising that the world has come to rely ever more heavily on knowledge-driven TFP gains (Fuglie et al. 2020). However, the rate at which knowledge capital is translated into TFP growth varies greatly across regions and is likely related to the agro-climatic environment in which innovations are being undertaken (IPCC 2014). This is a dimension of climate change which has received almost no attention to date by those seeking to quantify climate impacts on food security. How will higher temperatures and more variable rainfall affect the cost and success of future plant breeding?

The paper is organized as follows. We begin by introducing an analytical framework that permits a more comprehensive assessment of all of the factors affecting the growth in global food output, thereby putting climate impacts into the broader context. This allows us to consider the full range of inputs whose productivity might be affected by climate change. We then turn to a deeper input – namely knowledge capital – that underlies must of the recent growth in total factor productivity (TFP) in agriculture. Section five focuses on the question of product coverage, highlighting just how limited has been the focus on staple crops. We then turn to computational examples to illustrate the potential magnitude and importance of the missing climate impacts on agricultural production, food prices and economic welfare. The paper concludes with a discussion of future research directions.

2. Analytical framework

In order to assess the relative importance of different factors driving food production, both at a regional and global scale, we use the lens of an aggregate, agricultural production function: $Y = Af(\boldsymbol{X})$ where Y is aggregate agricultural output, $\boldsymbol{X}$ is a vector of inputs, and A is an index of Total Factor Productivity (TFP). In light of the fact that the agricultural sector is generally populated by a large number of producers, with relatively free entry and exit, we can use the result of Diewert (1981) to assert that the aggregate production function will exhibit constant returns to scale, regardless of the farm level technologies. Furthermore, assuming that farmers minimize costs, we can derive the following relationship between the change in individual agricultural inputs, X_i, expressed in percentage change form in lower case, x_i, and the percentage change in aggregate output, also in lower case, y. In addition to percentage changes in TFP (A in the production function), denoted with lower case a, we introduce the possibility of input-augmenting technological change, a_i:

$$y = a + \sum_i \theta_i(x_i + a_i) \tag{1}$$

In Eq. (1), $\theta_i = W_iX_i/PY$ is the cost share of input i, W_i is the input price, and P is the price of output. This cost share reflects the marginal productivity of input i due to the assumption of cost minimization by individual farms since this implies that: $f_i(X) = W_i/P$. Within this framework, climate impacts are introduced through the terms $a$and a_i capturing Hicks-neutral changes in total factor productivity (i.e., all inputs affected equally) and input-biased impacts that only affect the productivity of a specific input.

In addition to altering the production function directly through the technology terms, climate impacts can also alter relative prices. For example, a decline in seasonal precipitation may lead to a shortage of water locally, which, in turn, raises the price of water, W_i, thereby altering the cost minimizing use of irrigation. As a consequence, there is likely to be a change in the associated cost share, θ_i. If the elasticity of substitution between water and other inputs is less than one ($\sigma < 1$), then such an input price increase will increase the cost share of water, thereby rendering this an economically more important input in the overall production of food. This, in turn, will place a higher value on innovations which conserve water ($a_W > 0$). On the other hand, if existing technologies allow for a high degree of substitution between water and other inputs, then the cost share of water will fall when water becomes more scarce. In summary, there is an important interplay between prices in the economy and the impacts of climate change on food production that will arise endogenously as a function of climate change, or exogenously as a function of broader economic developments as conveyed to farmers through changing prices.

To obtain an analytical expression for the partial equilibrium change in food output in the face of climate change, we must augment this simple model of agricultural production in several ways. First of all, we add a downward sloping farm level demand curve for food, with elasticity $-\eta_D$. To reflect supply constraints, we add an upward sloping supply schedule for the land/water composite (simply call this land, denoted L for the sake of convenience) with land rental supply elasticity, ν_L. Next, we assume that capital, labor and intermediate inputs are in perfectly elastic supply over the long run (i.e., their input prices are dictated by the non-farm economy). Finally, we must specify precisely how the system is affected by climate change, i.e., which technology terms in (1) will be shocked: $a$or some combination of the $a_i$variables.

The most popular representation of climate change in general equilibrium models of agriculture (Robinson et al. 2014) involves shocking a_L with the size of the shock dictated by biophysical models' predictions of the change in yield as we move from current to future climate[1]. Partial equilibrium models have typically incorporated these climate-induced shocks as a shift in the yield function. The logic is that, if these crop models predict (e.g.) a 10% decline in yields under future climate, then that means that land will be 10% less productive. However, if none of the other $a_i$variables are perturbed, then these other inputs will remain as productive as before. This opens the possibility of substituting those inputs for land, the effective price of which (W_L/A_L)has risen. This characterization of climate change gives rise to the following equilibrium percentage change in output (Hertel et al., 2016):

$$y = (1 + \nu_L)\eta_D a_L/\eta \tag{2}$$

Where $\eta = \eta_D + \eta_S$ is the aggregate price responsiveness in the market (i.e., the sum of supply and demand elasticities). The two terms in the numerator of (2) capture the direct impact on output of the shift in land supply, $\eta_D a_L/\eta$, and the indirect effect through the impact of climate change on land rents and therefore on cropland use (hence the presence of the land supply elasticity), $\nu_L \eta_D a_L/\eta$. Clearly, if the biophysical models predict a future decline in yields, $a_L < 0$, output will fall. It will fall more, the more price sensitive is the farm level demand for food, and the more responsive is the land supply to agricultural returns.

3. Which inputs are affected by climate change?

Cost Shares as a Key Metric: As noted above, most of the existing literature has focused on changes in crop output per unit of land (i.e., crop yields) when characterizing climate impacts in agriculture. Before going further let us pause to think about the relative economic importance of land—the one input which has commanded the most attention from previous authors. With Eq. (1) in mind, the most natural way to undertake such a comparison across diverse inputs is through the relative size of their cost shares, θ_i. Estimates of cost shares may be obtained from econometric studies of agricultural production. These studies recognize that farms' choices of input intensities are endogenous and a function of relative prices. Furthermore, in any given year, there are many stochastic factors operating on the observed input costs (Ball 2006). The GTAP data base (Aguiar et al., 2019) reports national agricultural cost shares wherein the composition of national-level value-added is obtained regional econometric studies. Fig. 1 summarizes these cost shares aggregated to the level of the entire world, as well as for two very different regions: United States (USA) and Sub-Saharan Africa (SSA).

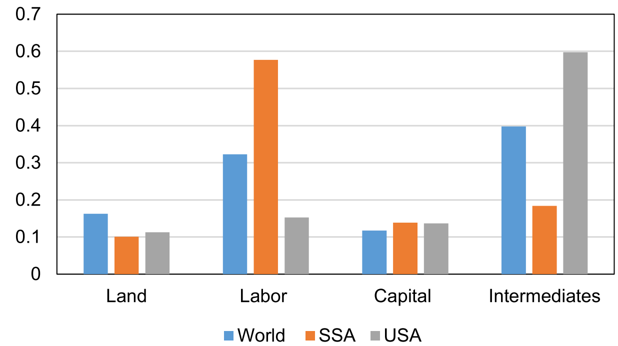

Fig. 1. Shares of inputs in total costs for agriculture, for select regions. Source: GTAP v.10 data base, Aguiar et al., 2019. Note the relative unimportance of land, relative to other inputs and the large share of labor in the SSA region.

There are several remarkable things about the estimates of agricultural cost shares shown in Fig. 1. First is the enormous difference in the share of intermediate inputs, and, by subtraction, the share of value-added in total costs. In the US, value-added (land, labor and capital) accounts for only 40% of input costs whereas in the SSA region, this share is more than 80%. Within the value-added composite, labor is dominant in the SSA region, followed by capital[2] and land. This suggests that anything that alters the productivity of labor in the region (e.g., heat stress) could have a dramatic impact on agricultural output. Further, if the heat stress impact in SSA is larger than in other regions, this effect will be magnified by the large labor cost share in that region. In the US, capital and labor exhibit comparable cost shares. In both regions, land is the least important input from the cost share point of view. (Although globally land's cost share is larger than that of the capital input.) The modest economic importance of the land input will be somewhat surprising to those who are used to thinking of agricultural production as being largely driven by land area. However, the declining relative importance of agricultural land in the economy was first highlighted more than 60 years ago by Nobel Laureate T.W. Schultz (1953). He emphasized the increasing importance of other inputs, in particular, skilled labor, capital and knowledge (in the form of new technologies). Indeed, the role of technological improvements in promoting agricultural production is a theme which will be explored in some depth below.

Climate Impacts as TFP Changes: An important conceptual question has to do with how we interpret the climate impact results emerging from biophysical models of crop production. As noted above, the predominant approach has been one in which the changes in yields predicted by crop models are treated as a perturbation to the productivity of land (a_L), leading to the long run equilibrium change in output reported in Eq. (2). But others have challenged this, suggesting a different thought experiment for incorporating the climate induced yield impacts

[1] A summary of key assumptions employed in a dozen global economic models used in the Agricultural Model Intercomparison Project (AgMIP) is provided in Table 1 of Hertel et al. (2016). Virtually all of the partial equilibrium models in AgMIP treated climate impacts as a shock to yields. The six general equilibrium models employed in AgMIP treated climate impacts as a partial factor productivity shock.

[2] When evaluating these cost shares it is important to recognize that these depend on both the quantity of the input used per unit of output and the price of the input, relative to output price. In the USA region, for example, capital is relatively abundant and this serves to dampen its cost share despite the capital intensity of the farm sector in USA. In the SSA region, capital is scarce, and this price effect tends to bolster the cost share, even though its intensity of use is lower.

into Eq. (1) (Hertel et al., 2010). For example, consider the case where, if the farmer engaged in exactly the same activities under the new climate (i.e., no climate-induced input substitution), then yields would be 10% lower. If both the land and the non-land input levels are unaltered in this thought experiment, then the output reduction of 10% is equivalent to a decline in a_i for ***all the inputs*** in Eq. (1). This, in turn, is equivalent to a Hicks-neutral productivity shock of -10%, i.e., $a = -10$. As we will see, this subtle difference in translation of the agronomic results into economic consequences has dramatically different food security implications.

Recent research has sought to directly estimate the impact of climate on TFP growth. Liang et al. (2017) estimated that regional variations in temperature and precipitation account for roughly 70% of variations in US TFP growth over the period: 1981–2010. Ortiz-Bobea et al. (2018) estimate the relationship between US state-level TFP growth and climate variables over the period 1961–2004. They find that certain regions of the country are becoming more sensitive to climate due to their changing mix of outputs. Agricultural TFP growth in the Midwestern US, in particular, has become more climate-sensitive due to increased emphasis on corn and soybean output.

Adopting the TFP view of climate impacts, we now solve the same partial equilibrium model as before for the long run change in food output under a Hicks-neutral productivity shock to obtain:

$$y = (1 + \eta_S)\eta_D a/\eta \tag{3}$$

Where the elasticity of commodity supply is the sum of the extensive and intensive margins of supply response: $\eta_S = \theta_L^{-1}\nu_L + \sigma(\theta_L^{-1} - 1)$. In this expression $\theta_L^{-1}$is the inverse of the cost share of land and σ is the elasticity of substitution between land and other inputs governing the scope for intensification (or de-intensification) of agricultural production. Comparing (3) and (2) we see that, even ignoring the possibility of variable input substitution for land (assuming $\sigma = 0$), the inverse cost share applied to the land supply elasticity, ν_L, will sharply magnify the impact of this climate shock on agricultural output. For example, taking the USA cost share of land from Fig. 1 as roughly 0.10, *this implies a tenfold magnification effect* when the yield shock is interpreted as a perturbation to TFP.

How can this be? To gain a better understanding, consider the zero-profit condition which is dual to Eq. (1):

$$p + a = \sum_i \theta_i(w_i - a_i) \tag{4}$$

A negative shock to TFP operates like a decline in output price in this expression, thereby dampening profitability. In the long run, with other input prices dictated by the non-farm economy, all of this diminished profitability must be borne by the quasi-fixed factors of production – in this case land (although other factors may also be in limited supply, in which case their cost share should also be included in this calculation). Therefore: $w_L = \theta_L^{-1}(p + a)$. This is source of the magnification effect noted above. Since the long run prices of the other inputs are dictated by the non-farm economy, all of the adjustment must occur in the returns to the quasi-fixed factor (land). Adding to this magnification effect the potential for a response at the intensive margin of supply, through the second term in the supply elasticity, $\sigma(\theta_L^{-1} - 1) \geqslant 0$, it is clear that the decision about whether it is just land productivity that is affected by climate change is a critical one deserving careful scrutiny and further empirical investigation.

Heat Stress and Labor Capacity in Agriculture: Beyond the agronomic assessments of climate impacts on plant growth, there is now mounting evidence that global warming will sharply reduce labor capacity – particularly when workers are outdoors and exposed to solar radiation (Kjellstrom et al. 2016). Research in this area has been advancing rapidly and is summarized in the *Annual Reviews* paper by Buzan and Huber (2020). Those authors emphasize the importance of considering the combination of heat and humidity as presenting a significant threat to human's ability to function, since, in the presence of high humidity, the human body has great difficulty releasing internally generated heat. The US military developed a metric to address the risk posed to personnel from prolonged exposure to the combination of high heat and humidity (Minard et al., 1957). It is called Wet Bulb Globe Temperature (WBGT) and has also been adopted by the International Standardization Organization (ISO) to measure workplace heat stress (Parsons 2006). While WBGT has not been computed at global scale based on climate model outputs, a simplified version of this measure (sWBGT) has been incorporated into climate models (Buzan et al., 2015).

Buzan and Huber (2020) use the sWBGT measure, in combination with the Dunne et al. (2013) equation for determining labor capacity, to compute global gridded labor capacity in their end of 20th century baseline (deemed to be current climate) as well as for a world in which there is an average of + 4 degrees C global warming. In their baseline, current global annual (population-weighted) labor capacity is estimated to be 80% with regional averages varying from 98% in the high latitudes (i.e., almost no constraints) to 71% in the tropics (significant capacity limitations under current climate). At + 4 degrees C, the global average drops to 59%, with labor capacity in the tropics falling to 40%. This is a dramatic shock to the productivity of labor and it is indicative of the kinds of productivity losses that are likely to occur on non-mechanized farms where workers are exposed to direct solar radiation. Even in the US, where agriculture is highly mechanized – particularly for row crops, the impact on workers cultivating and harvesting specialty crops has been shown to be significant (Stevens 2017).

Lima et al. (Lima et al. 2020) incorporate the combination of sWBGT estimates from a suite of climate models into the GTAP model of global trade and production. In terms of Eq. (1), these are treated as shocks to a_i, i.e., partial factor productivity losses applied to labor. The authors proceed to compare the welfare cost of these labor capacity losses to the losses based on a *meta*-analysis of IPCC studies of crop yield losses (Moore et al., 2017a). Importantly, in that prior study, the yield losses were treated as total factor productivity shocks (perturbations to a). Even with this aggressive interpretation of crop yield impacts, Lima et al. (2020) find that global welfare losses at + 3C were comparable between the two scenarios (a_i shocks to labor capacity vs. a shocks to crop productivity). Furthermore, they find that the distribution of losses from these two sets of climate impacts are quite different, with the labor capacity losses concentrated in Southeast Asia, South Asia and Sub Saharan Africa. In short, ignoring the impacts of combined heat and humidity on labor capacity paints a very distorted picture of how climate change affects agriculture. And, it greatly understates the adverse impacts in some of the world's poorest countries.

Orlov et al. (2020) offer a similar analysis of the impacts of heat stress on labor capacity across the entire economy, with differentiated consequences for agriculture and construction (most severe due to exposure to direct sunlight and high effort), manufacturing (less severe due to shade from the sun and moderate work effort) and services (least affected due to shade and low work effort). They also incorporate an assumption of increased mechanization (thereby leading to lower effort) in agriculture and construction as per capita incomes rise. As with Lima et al., these authors find that countries in Africa, South and Southeast Asia are most severely affected, with agriculture and construction showing the largest drops in output.

Pests, weeds and disease: Both global warming and elevated CO2 concentrations are likely to affect biotic stresses (Ziska et al. 2011). Invasive weeds tend to be more responsive than crops to changes in resource availability. Higher temperatures reduce the latency period for plant pathogens, thereby speeding up their rate of evolution and with it their capacity to adapt to the new environment (Cairns et al. 2012). Insects are highly dependent on temperatures and thrive with a warming environment (Bale et al. 2002). Diminished frost frequencies can expand the ranges of many important pests and diseases affecting agriculture as has been documented for the case of potato blight in Finland (Hannukkala et al. 2007) and for kudzu weed in the US Corn Belt (Ziska et al. 2011).

Changes in agroecological conditions also elicit adaptation responses from producers which can affect the mix of inputs employed as well as agricultural productivity. In a recent study of maize producers in Kenya, Jagnani et al. (Jagnani et al. 2020) find that, when confronted with warmer than normal temperatures during critical growing periods, farm households increase the application of pesticides (often at the expense of fertilizer) as well as increasing the use of labor for weeding. In addition to the increase in direct labor requirement, there is likely to be a further burden on labor due to the adverse health impacts of increased pesticide use (Sheahan et al., 2017). In terms of the analytical framework laid out above, the effects of climate change on the Kenyan maize farms may be viewed as a new technology that is both labor- and pesticide using ($a_i < 0$) and therefore a drag on farm output growth.

Other Inputs: Just as humans are affected by the combination of heat, humidity and solar radiation, so too are animals (Mader, 2014). And, in much of Africa, these remain an important source of draft power – an input that appears in the capital cost share in the poorest countries of the world. Yet, to our knowledge, there have been no studies quantifying this effect. One of the challenges is the huge variation in animal species (vs. the studies of the more uniform *homo sapiens* species referred to above). Of course, livestock products also represent an important agricultural *output* – a point to be discussed below.

There is also little evidence available about how the productivity of intermediate inputs will be affected by climate change. In the richest economies, where there is significant R&D capacity and a well-developed private sector supply chain for delivering modern inputs to farmers, there is considerable scope to adapt the characteristics of these intermediate inputs to a changing climate – including new seed varieties as well as improved pest control. However, in the world's poorest countries, the small cost share for commercial inputs belies the lack of private sector investment in this area and it seems unlikely that there will be rapid adaptation of these inputs to changing climatic conditions.

While labor and land may become less productive under climate change, irrigation water is an input for which the marginal value product may actually rise. This could help offset some of the other, adverse impacts of a warming climate. Haqiqi et al. (2019) estimate the marginal value product of additional soil moisture (via irrigation) in corn production and find that this depends on the initial state of soil moisture as well as commodity prices. In a season with high heat and low rainfall, as well as elevated commodity prices, the value of applying additional irrigation water can be very high. Provided supplemental irrigation water can be obtained, it can play an important role in mitigating yield losses (Schlenker and Roberts 2009).

4. Knowledge capital

The preceding discussion has missed one of the most overlooked inputs into the growth in agricultural output: knowledge capital. To understand the growing importance of knowledge capital in the evolving agricultural economy, consider Fig. 2, produced by USDA-ERS (2019). Isolating TFP growth on the left-hand side of Eq. (1), and applying FAO data on inputs and outputs from 1961 to the present, the authors have obtained an estimate of the historical growth rate in Hicks-neutral TFP growth as a residual: $a = y - \sum_i \theta_i x_i$. Combining these TFP estimates with observed input growth rates over this period, the individual sources of global agricultural output growth can be decomposed (Fig. 2). From the decadal averages reported in Fig. 2, it is clear that the sources of growth in food production have changed dramatically since the 1960′s when it was largely driven by input intensification. Since 1990, TFP has become the dominant source of growth in agricultural output. Like much of the rest of the modern economy, agriculture is now knowledge-driven (Fuglie 2018).

Fuglie (2018) formally explores the role of knowledge capital in the evolution of TFP around the world. Following earlier work by Alston et al. (2010), he postulates that A in Eq. (1) is itself a function of knowledge capital in the innovating region, as well as in other 'spillover regions', as shown in the following equation:

$$A = A_O R_O^{\delta_O} R_S^{\delta_S} \tag{5}$$

where initial productivity, A_O, is enhanced by growth in the stock of own-research capital, R_O , and spill-in research capital, R_S with the elasticities δ_O and δ_S governing the responsiveness of TFP to these investments. He surveys the literature aimed at estimating these elasticities, on a region-specific basis, and uses these empirical estimates, along with Eq. (5), to provide an attribution of TFP growth, by region, to knowledge capital. In so doing, he assumes a specific lag structure

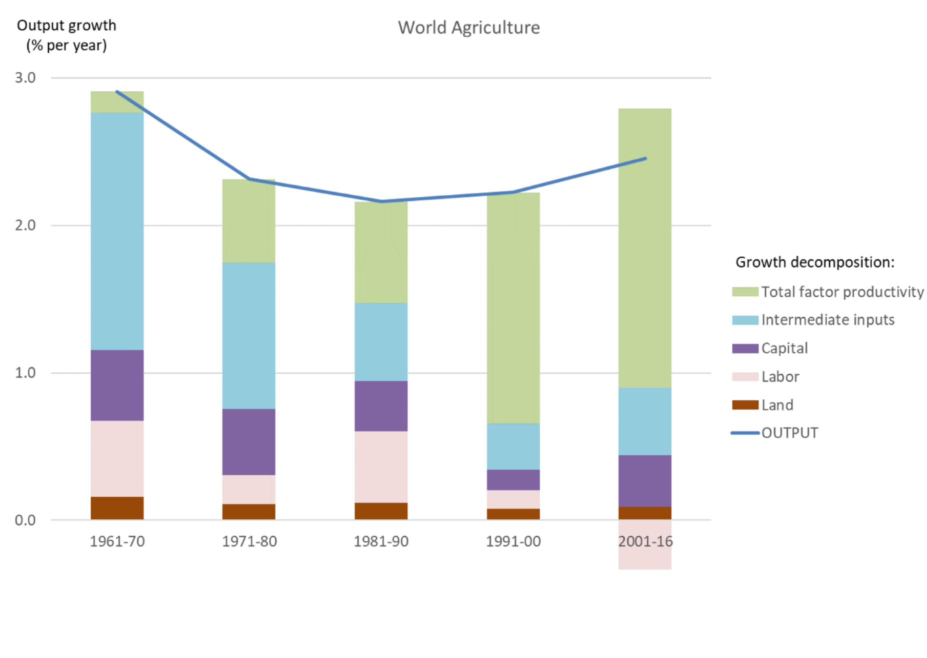

Fig. 2. Sources of global agricultural output growth, by decade, 1961–2016. Source: USDA-ERS (2019). While input intensification was key in the early decades (1961–90), TFP growth is the dominant driver in more recent decades.

through which the impact of knowledge capital rises through time, peaks, and then declines as the value of this knowledge depreciates. The lag between R&D spending and TFP growth can be very long. For example, Baldos et al. (2019) estimate that, in the United States, over the course of the 20th century, the productivity impact of public R&D investments in agriculture did not peak until 22 years following the initial investment. They also find that the knowledge capital depreciated relatively slowly over this period, with lingering impacts in the fifth decade after the money was spent. (Not surprisingly, this closely mirrors the career profile of scientist!) Using this framework, Fuglie (2018) is able to explain a large share of the TFP growth between 1990 and 2011 in the OECD countries as well as Latin America and South Asia. (In other regions, such as China, economic reforms also played a key role in boosting TFP.)

Within this framework, there are two distinct pathways for climate impacts to be felt. First, climate change could accelerate the rate of depreciation of existing knowledge capital – thereby depleting the stocks on the right hand side of Eq. (5). This, in turn, will slow future TFP growth. The second channel is through the elasticities in Eq. (5). Based on Fuglie's (2018) survey of the literature, there is tremendous variation in these elasticities across regions – ranging from 0.07 for public R&D spending in developing countries to figures in excess of 0.30 in the US. Surely much of this variation can be explained by infrastructure, proximity to top research scientists and institutional stability and governance. But agro-climatic conditions in some regions are likely to pose more significant challenges than others. In the tropics, temperatures are already close to, or perhaps beyond, their agronomic ideal. Increasing this threshold via tolerance to heat stress is likely to prove more challenging than other measures aimed at boosting yields (Fischer and Byerlee, 2014). Therefore, it seems reasonable that climate change might reduce these elasticities, thereby slowing future TFP growth, for any given knowledge capital pathway.

The pathways for climate change to alter the rate of depreciation in knowledge capital, or reduce the elasticities in Eq. (5), have received no formal analysis to date, yet this could be critically important due to its implications for long run growth. It is notable that, in their review of climate impacts and adaptation for the IPCC, Working Group II alludes to the possiblity that rising temperatures and uncertain rainfall are likely to make future innovation more difficult. They go so far as to speculate that, at mid-century, climate change could remove one year of productivity growth over the course of each decade – or about a 10% reduction in the rate of growth in knowledge-driven productivity (IPCC, 2014). This type of impact will accumulate gradually over time, with long-lasting implications. In short, this is an area crying out for empirical research. This problem is particularly important, given the long lag between R&D spending today and future TFP growth. If decision makers seek to offset a potential climate change-driven slowdown in TFP at mid-century, R&D investments will need to be made in the coming decade. Cai et al. (2018) explore this problem of irreversible investment in public R&D, in the face of long lags between that spending and TFP growth, in the context of uncertain climate as well as uncertain population and income growth. They conclude that the best path is likely to be one in which near term R&D spending is based on food scarcity (pessimistic) scenarios, with higher current levels of spending than might otherwise be considered optimal.

5. Product coverage

Closely related to the issue of geographic coverage is the question of product coverage. The FAO identifies 175 distinct crops, yet the vast majority of research on climate impacts in agriculture has been undertaken on just 4 crops – the main staples: maize, wheat, rice and soybeans. Indeed, of the 1782 climate impact yield estimates (from 94 independent studies) reported to the IPCC for the AR5, these four crops accounted for 1165 of the total (74 of the 94 studies) (Challinor et al. 2014). And the remaining studies were so thinly spread that a statistical

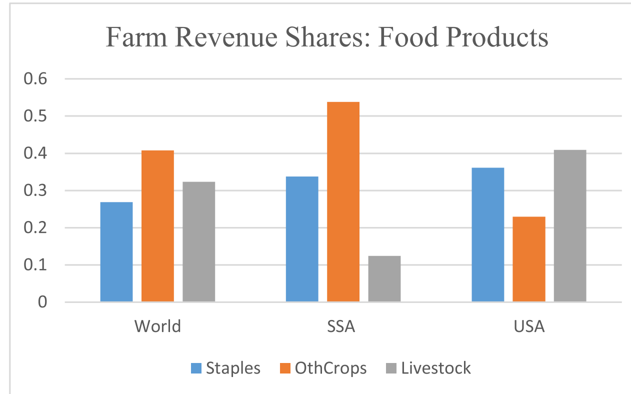

Fig. 3. Share of food product categories in global agricultural sales: Source, GTAP 10 data base, Aguiar et al., 2019. Note that staple crops account for just over one-quarter of global agricultural revenue.

meta-analysis of climate impacts was not possible beyond these four major crops (Moore et al., 2017a). From a caloric point of view, these four crops are also indeed dominant, accounting for nearly two-thirds of global caloric consumption (FAO 1995). However, from a broader nutritional point of view, other crops which are rich in micro-nutrients – particularly fruits and vegetables, as well as livestock products which bring much needed protein to the diets of the poor – are increasingly important and these are largely missing from the climate impacts literature.

Analogously to the input aggregation applied above, the proper economic metric for aggregation and comparison of outputs is that of revenue shares (assuming revenue maximization on multi-product farms). Fig. 3 provides data analogous to that in Fig. 1, but now reporting output revenue shares for agriculture. Each bar in the figure reports the share of total agricultural revenue accounted for by a given product category, by region. We can see that, accounting for about one quarter of global agricultural sales, the grains and oilseeds (staples) sector is hardly dominant. Indeed, other crops are more significant, accounting for nearly one-third of global farm output. And the global value of livestock output is even higher. Furthermore, livestock are susceptible to heat and humidity in the same way as humans. Heat stress reduces feed intake and results in diminished productivity (Key and Sneeringer 2014). Clearly, the dominant focus on grains and oilseeds in the climate impacts literature reflects a serious imbalance.

Recent work by Chambers and Pieralli (2020), Ortiz-Bobea et al. (2018) and Liang et al. (2017) circumvent the problem of excessively narrow interpretations of agricultural output by focusing on climate impacts on the entire agricultural sector. This is typically a necessity when measuring the impacts of climate on TFP, since many agricultural inputs (e.g., labor, capital) are effectively non-allocable, i.e., it is not possible to establish how much of these factors are applied to each output on a multi-output farm. Ortiz-Bobea et al. (2018) explore the sub-sector impacts of climate on productivity by examining the impact of climate on crop and livestock output aggregates. Since this ignores the role of input adaptations, it is an imperfect, but useful approach to understanding the differential climate sensitivities of agricultural outputs. Of particular interest is their finding that the livestock and specialty crops sectors appear to have been far less influenced by climate change than have the row crops sectors.

6. Climate impacts on nutrition

The consequences of climate change for aggregate caloric availability have been well-documented, primarily in the context of studies of changing yields for staple grains and oilseeds (Schlenker and Roberts 2009). However, recent evidence suggests that elevated CO2 concentrations in the atmosphere could significantly reduce the nutrient density of crops. Smith and Myers (2018) analyze the impacts of reaching 550 ppm atmospheric CO_2 for the protein, iron and zinc content of all major crops. They find that these densities are likely to fall by 3–17%. Assuming 2050 demographics and unchanged diets, this would result in 175 million additional zinc deficient individuals and 122 million more protein deficient people globally. Reductions in dietary iron could be particularly problematic for women of child-bearing age and young children in Asia and parts of Africa where the prevalence of anemia is already very high. While changes in diet may limit some of these impacts, this is a wake-up call for those working on global nutrition. More attention to the implications of climate change for micro-nutrient consumption is clearly important.

7. Computational illustrations

We conclude this overview of climate impacts on agriculture with a set of global economic simulations, drawing on the previous work of Moore et al. (2017a, 2017b) and Lima et al. (2020). Those authors have documented the impact of climate driven shocks to crop yields as well as climate driven shocks to labor productivity. Here, we draw on their models and climate-induced productivity shocks to illustrate the issues raised in the foregoing discussion.

Both sets of authors used the version 7 GTAP model and version 9 GTAP data base (Aguiar et al., 2016; Corong et al., 2017) to assess the impacts of climate change on production, consumption, trade and welfare. Individual sectors in the standard GTAP model have the same structure as the analytical partial equilibrium model detailed in Eqs. (1)–(4). However, since GTAP is a general equilibrium model, the farm-level demand elasticity in any given region is a function of both domestic and foreign demands (including intermediate as well as final consumption) as well as supply response in the rest of the world. I.e., when viewed from a regional perspective, this demand response is now an excess demand elasticity – referring to the excess of rest of world demand, over and above their own supplies. Furthermore, the supply of non-land factors of production – treated as perfectly elastic in Eqs. (2) and (3) – is now constrained by national market clearing conditions in this general equilibrium model. Therefore non-land input prices are now endogenous.

Experimental Design: Table 1 provides the design for our four computational experiments. They involve varying commodity coverage of the impacts (staples vs. all crops), as well as varying the type of productivity shock (partial factor productivity impacts on land or labor, as in Eq. (2) vs. total factor productivity impacts as in Eq. (3)). From Moore et al. (2017a, 2017b), we have *meta*-analysis-based estimates of the impacts of climate change on staple crop yields for various levels of global warming. (As noted previously, there are insufficient data points for the other 171 FAO crops to allow for a *meta*-analysis outside of these staple crops.) Here, we focus on warming of + 3C and utilize the authors' median estimates of yield impacts. The labor impacts are estimated following the methodology outlined in Lima et al. (2020), using the combination of the sWBGT measure of heat and humidity and the NIOSH method for estimating human labor capacity.

Comparing experiments E1 and E2 in Table 1 allows for a comparison of the all-input (TFP) interpretation of yield impacts versus the land-only partial factor productivity impacts approach. Contrasting the labor and land partial factor productivity shocks (E2 and E3) allows us to explore the relative importance of these two types of climate impacts.

Table 1
Experiment Design.

	Input Coverage		
Product Coverage	All	Land	Labor
Staples	E1	E2	E3
All Crops			E4

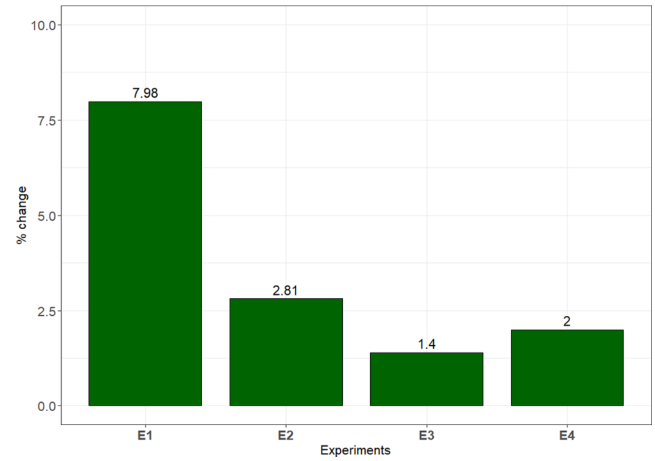

Fig. 4. Impact of climate change experiments on the composite price of staple grains and oilseeds. E1: Staple-TFP; E2: Staple-Land; E3: Staple-Labor; E4: All-Crops-Labor. Source: Authors calculations. Note that treating climate change impacts via TFP results in much larger food price impacts.

Finally, while we don't have yield impact estimates for non-staple crops or for livestock, we can explore the consequences of expanding product coverage in the case of labor productivity shocks, and for this, we contrast experiments E3 and E4.

Aggregate food price effects: The impact of the experiments in Table 1 on agricultural prices can be readily anticipated from Eq. (4). Since the cost shares in this expression, θ_i, are less than one (recall Fig. 1), the impact of the partial factor productivity shocks on price will necessarily be diluted. This effect is evident when we compare the change in the composite staple grains and oilseeds price reported in Fig. 4 across experiments E1 and E2. Of course, the difference in commodity price changes between the two experiments is less than that suggested by the land cost shares in Fig. 1, since other input prices also change in general equilibrium.

The impact on staple food prices of the partial factor productivity labor shock (due to heat stress limiting humans' capacity to work) is even more modest than the shock to land productivity (E3 vs. E2) since additional labor can be brought into the sector more readily than can land (i.e., the labor supply to agriculture is more elastic than is land supply). Furthermore, expansion of the labor shocks to other crops sectors in E4, while boosting the staples price impact somewhat, still

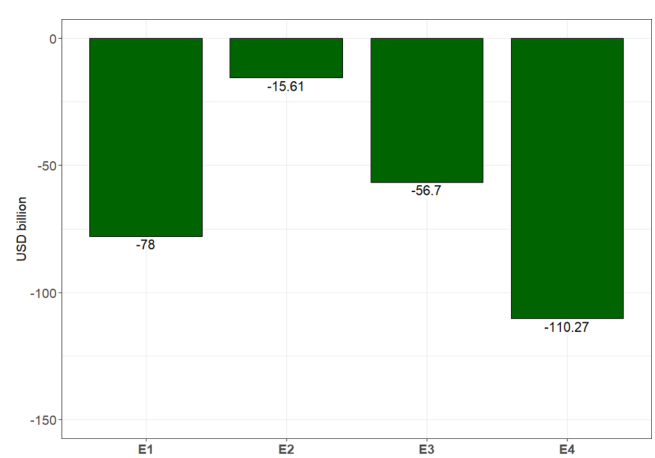

Fig. 5. Impact of climate change experiments on global welfare. E1: Staple-TFP; E2: Staple-Land; E3: Staple-Labor; E4: All-Crops-Labor. Source: Authors calculations. Note that labor productivity impacts (E3) are far more damaging to global welfare than are land productivity impacts (E2) obtained from yield estimates.

does not reach the level of the partial factor land shock. The fact that there is such a large difference in the staple food price effects of the two rival interpretations of agronomic yield change estimates (E1 vs. E2) is a cause for great concern, as there has been almost no discussion of these competing approaches.

Aggregate welfare effects: The cross-experiment comparison is quite different when we focus on global welfare impacts (Fig. 5). Here, we see that the global welfare loss suffered when the climate shocks to yields are applied across all inputs (TFP reduction) is far greater than that when only land productivities are affected. However, when we compare the welfare loss from partial factor productivity reductions for land only, vs. labor only, the latter is now dominant. Furthermore, in the case of welfare impacts, as the extent of labor productivity losses broadens from staples to all crops, the losses increase sharply. This makes sense, since, unlike the staples price index, welfare is an economy-wide measure, so the more sectors are affected, the larger the impact.

To gain deeper insight into these results, we turn to Eq. (6) which provides an analytical decomposition of regional welfare changes in general equilibrium, measured as Equivalent Variation for a given region s (EV^s). (See Huff and Hertel (2001) for the derivation of this expression.) The climate change induced productivity shocks (in percentage change) are represented by a^{is} in the case of TFP shocks to sector i in region s, and a_j^{is} in the case of partial factor productivity shocks to input j employed in sector i in region s. The first term in this expression states that, if farmers plant the same crop using the same mix of inputs at mid-century, but harvest 1% less output, then the direct economic loss is equal to 1% of the value of output ($P^{is}Y^{is}$) of commodity i in region s. The second term in (6) captures the impact of the partial factor productivity shocks. Here, a 1% loss in (e.g.) labor capacity induces a direct welfare loss which is valued at 1% of the cost of labor employed in that sector ($W_j^{is}X_j^{is}$). These first two terms comprise the direct (first-order) welfare impacts of climate change. To translate these dollar changes into welfare terms, they must be multiplied by the EV scaling factor, (ψ_s), which is itself a function of the elasticity of expenditure with respect to utility.

$$EV^s = (\psi^s)\left\{\begin{array}{c} \sum_{i=1}^{N}(P^{is}Y^{is}(a^{is}/100)) \\ +\sum_{i=1}^{N}\sum_{j=1}^{M}(W_j^{is}X_j^{is}(a_j^{is}/100)) \\ +\sum_{i=1}^{N}(\tau^{is}P^{is}dY^{is}) \\ +\sum_{i=1}^{N}\sum_{r=1}^{R}(E^{isr}dPFOB^{isr}) \\ -\sum_{i=1}^{N}\sum_{r=1}^{R}(M^{irs}dPCIF^{irs}) \end{array}\right\} \tag{6}$$

Since the cost shares of labor and land are less than one, $\theta_i = W_iX_i/PY < 1$, it is hardly surprising that the aggregate welfare impacts of the partial factor productivity shocks are only a fraction of the TFP-driven welfare impacts. Somewhat more surprising, in light of the fact that the global cost shares of labor and land are quite similar (recall Fig. 1), is the much larger welfare impact from the labor vs. land partial factor productivity shocks. Deeper investigation into the source of this discrepancy reveals that, while the agronomic-based yield shocks are quite variable, depending on the crop, climate and location, the labor capacity reductions are uniformly negative (Fig. 6). Furthermore, the labor losses are greatest, precisely in those regions where labor cost shares are relatively high, particularly for rice production in Asia (Fig. 6). The other point that emerges from Fig. 6 is that in the most heat/humidity stressed regions of the world, where labor capacity losses are largest, the plants seem to fare better than the people under warming. This is particularly true for rice production in Southeast Asia (SEA) where the yield impacts are modest – rice has a high optimal growing temperature – but the labor losses are quite significant.

To investigate the plants vs. people impacts more fully, we turn to Fig. 7 which reports the impacts on output by region for rice (left hand panel) and wheat (right hand panel). Rice is relatively well-adapted to warm, humid climates, with a high agronomic optimal temperature. Estimated yield losses under global warming are concentrated in South and Southeast Asia, while Europe, Japan, South America and Australia are projected to experience higher yields under + 3C warming. This is reflected in the red portion of the output change bars in the figure for rice. This contrasts sharply with the labor impacts (green bars). While rice thrives in a warm, humid environment, the combination of heat and humidity is deadly for humans who can no longer dissipate their

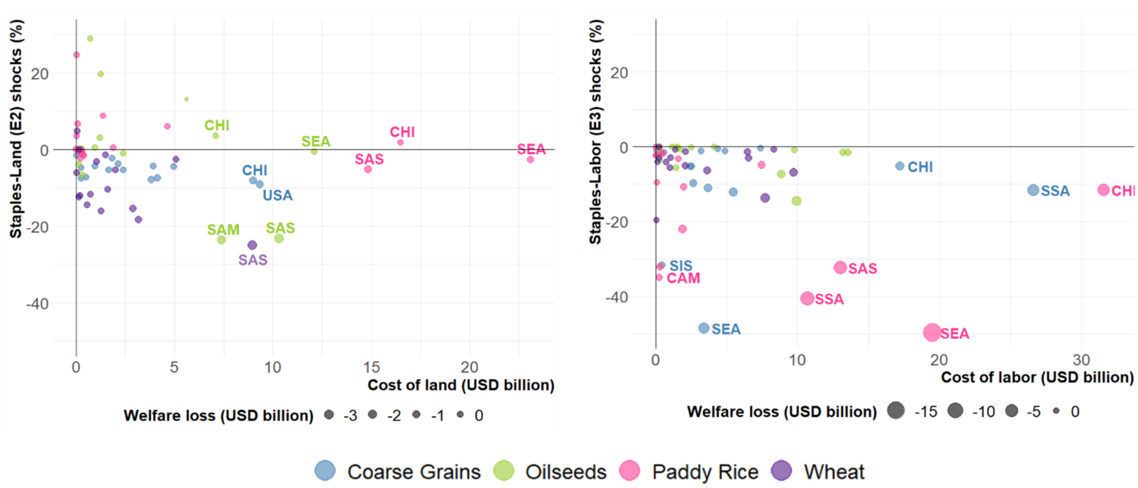

Fig. 6. Cost of climate-affected agricultural inputs used in staple crops production. Land (E2: left hand panel) and Labor (E3: right hand panel) induced welfare changes (horizontal axis) are each plotted against the shock to partial factor productivity of land and labor, respectively (vertical axis). The area of the circles denote the welfare loss associated with each crop-input-region combination. Crop losses are color-coded by sector. Note that the labor shocks are all negative and illustrate that some plants (e.g., rice in SEA) are better adapted to heat stress than are humans.

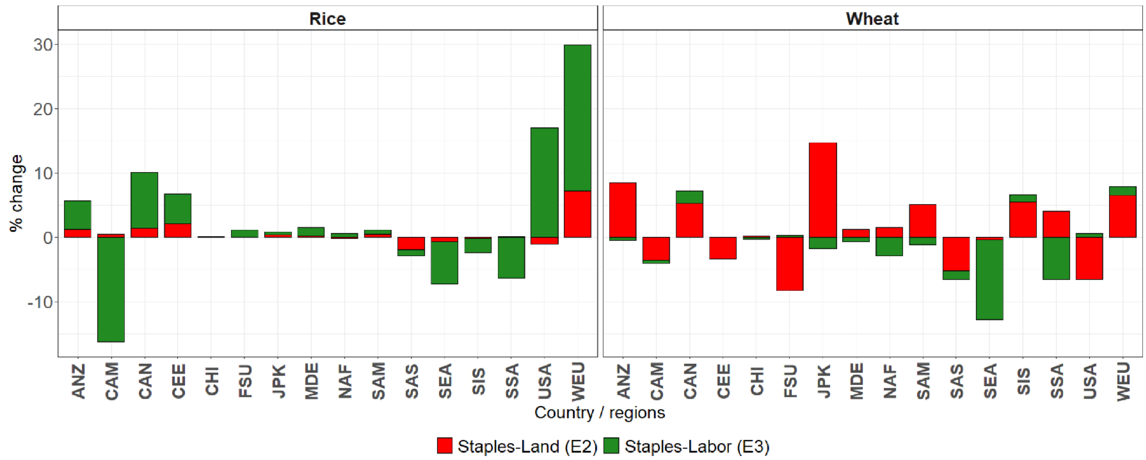

Fig. 7. Impacts of land (E2) vs. labor (E3) climate impacts on staple crops output by region: Rice (left panel) and Wheat (right panel). Note that the labor shocks dominate for rice production whereas the land (yield) shocks dominate for wheat which is largely grown in cooler climates. Country/regions: **USA**: United States; **CAN**: Canada and Rest of North America; **WEU**: Western Europe; **JPK**: Japan and South Korea; **ANZ**: Australia and New Zealand; **CEE**: Central and Eastern Europe; **FSU**: Former Soviet Union; **MDE**: Middle East; **CAM**: Central America; **SAM**: South America; **SAS**: South Asia; **SEA**: Southeast Asia; **CHI**: China plus (China, Hong Kong, North Korea, Macau, Mongolia); **NAF**: North Africa; **SSA**: Sub-Saharan Africa; **SIS**: Small Island States.

internally generated body heat under such conditions. Thus, the impacts of climate change on rice production through the labor input are much larger than that through the agronomic channels (compare the green with the red bars in Fig. 7). Despite the fact that all regions of the world experience diminished labor productivity in rice production, those experiencing the more modest impacts (North America, Europe, Australia) increase rice production in order to make up for the large declines in rice output in Central America, Asia and Africa.

The differential impact of climate change on wheat yields vs. labor employed in cultivating wheat is quite different from rice, as shown in the right hand panel of Fig. 7. Wheat has a much lower optimal agronomic temperature. Furthermore, it is often grown in dry, cooler regions of the world. As a consequence, the labor impacts are more modest than for rice. Therefore, the wheat output impacts of a changing climate are much more dramatic in the agronomic-based scenarios (Staples-land). Southeast Asia and SSA are exceptions, but these are not major wheat producing regions.

The remaining terms in Eq. (6) are the result of indirect (second-order) effects flowing from changes in equilibrium quantities and prices in the wake of direct climate impacts. The third term in (6) captures the interplay between climate change impacts and government policies. For example, if the climate impacts cause shrinkage in a sector ($dY^{is} < 0$) that is subsidized ($\tau^{is} < 0$), then there will be an efficiency gain in general equilibrium, as resources are re-allocated to higher value uses ($\tau^{is}P^{is}dY^{is} > 0$). (In the GTAP model, this allocative efficiency effect comprises thousands of terms, reflecting the plethora of existing distortions in the economy – not just those related to output taxes or subsidies.)

The final two terms in (6) refer to the terms of trade effects on regional welfare. The most hard-hit regions under climate change will reduce production, which, in turn, will cause their prices to rise, relative to the world average. (This model reflects the fact that agricultural products are not homogeneous. Rather they are differentiated – in this case by region of origin, as first pointed out by Armington (1969).) With export prices rising, relative to import prices, those hard-hit regions ($dPFOB^{isr} > dCIF^{isr}$) which are significant net exporters of climate-impacted commodities ($E^{is} > > M^{is}$), are expected to see large terms of trade gains. However, since this component of the welfare change simply amounts to income transfers amongst regions, when summed over all regions in the world, this effect washes out and therefore has no influence in the global welfare impacts reported in Fig. 5. Overall, the direct effect of climate change accounts for about 90 percent of the global welfare change in all of our experiments, with the allocative efficiency effects accounting for the remainder (roughly 10 percent of the global welfare impact).

Fig. 8 reports the geographic distribution of the full regional welfare impacts (i.e., considering all of the terms in Eq. (6)) stemming from the land and labor partial factor productivity shocks to staple crops (E2 and

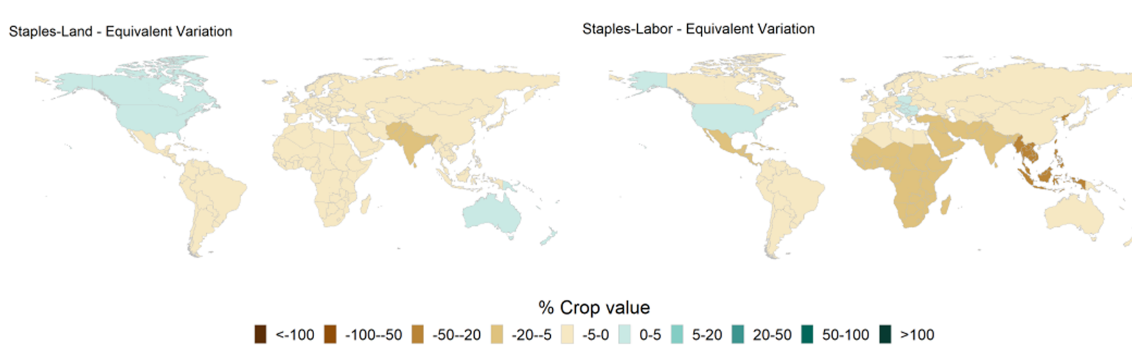

Fig. 8. Impact of climate change experiments E2 and E3 on the regional welfare. Changes are relative to the 2011 baseline. The maps show the total welfare changes reported as equivalent variation for Staples-Land and Staples-Labor experiments. Welfare changes are normalized by the value of crop production of all staple crops. Source: Authors' calculations. Note that the labor shocks induce greater losses in the tropics – particularly Africa, the Middle East, South- and Southeast Asia.

E3, respectively). Contrasting the two panels, we see that the losses in Southeast Asia and Sub-Saharan Africa stand out when labor capacity reductions are taken into account. Central America and the Middle East also contribute significantly to the global welfare losses under the labor stress experiment. In the labor stress experiment (E3: Staples-Labor), the benefitting regions are fewer, and these gains are driven by improvements in the regions' terms of trade, not by productivity gains, in contrast to the yield-based experiment (E2: Staples-Land).

8. Discussion and conclusions

The purpose of this paper is not to provide comprehensive new estimates of the food price and welfare impacts of climate change in agriculture, but rather to highlight the extent to which those of us in the climate impacts community have been effectively 'looking for our keys under the streetlight'. The majority of the research to date on climate impacts in agriculture has focused solely on four staple crops, accounting for only about one-quarter of the total value of agricultural output. Furthermore, when it comes to assessing these impacts, the sole focus has been the productivity of the cropland input employed in farming, which itself accounts for only about 16% of total production costs. Viewed from the entirety of the global agricultural sector, this means researchers have been focusing on only 4% (0.25 * 0.16 * 100%) of the economic value of global farming. What about the other 96%? This paper offers some evidence of significant impacts outside of the staple crops domain. In particular, the workers employed in agriculture are likely to be adversely affected by a warmer, more humid climate, and, in some regions, these 'people' impacts are much larger than the impacts on the plants themselves. It is time to move beyond assessing yield impacts for staple commodities where we have the best models and data, and venture into the realm of other food products as well as other farm inputs and nutritional impacts.

We also identify a significant discrepancy in the literature pertaining to how the agronomic yield shocks are implemented in economic models. Depending on whether these yield impacts are interpreted as a reduction solely in the productivity of land, or whether adverse yield impacts should be interpreted as a shock to all factors employed in crop activities, makes a big difference. This is particularly striking when it comes to the ensuing food price impacts – a key aspect of the climate/food security debate. Since the null hypothesis of no climate change impact on non-land input productivity is a testable hypothesis, the differences highlighted in this paper should provide ample motivation for future empirical work.

One aspect of climate impacts on agriculture that has received next to no attention relates to the consequences for productivity enhancement through agricultural research and development. As agriculture becomes increasingly knowledge-driven, the linkage between investments in science – quantified through the accumulation of knowledge capital – and future growth rates in agricultural productivity is central to global food and environmental outcomes. Current evidence suggests that this linkage – quantified as the elasticity of productivity growth with respect to knowledge capital – is greater in highly developed, temperate regions (Fuglie 2018). If global warming results in a reduction in this elasticity – in both rich and poor countries – due to challenges posed by higher temperatures, then climate change could have a significant long term, dynamic impact on food output, resulting in higher food prices and reduced real incomes by mid-century.

All of this raises a question about the possibility of finding other streetlights to illuminate the broader climate impacts landscape. When it comes to extending climate impact analysis of crop yields beyond the staple grains and oilseeds, there are essentially two avenues: process models and statistical modeling. The good news is that, when done well, the two approaches appear to find the same climate sensitivities for staple crops (Lobell and Asseng 2017). However, since the development of a valid process model for a new crop is quite resource intensive, those authors conclude that statistical models are likely the quickest way to broaden the crop yield 'streetlight', particularly when applied to crops beyond the major grains.

We expect that research into the impacts of heat stress on agricultural workers will be a 'hot topic' in the coming years. There is already important work underway in this area in non-agricultural settings (Heal and Park, 2016; Zander et al., 2015; Kjellstrom et al., 2016; Zhang et al., 2018). Of course, agricultural work is different. Work effort is generally higher than in manufacturing or services jobs and exposure to sunlight heightens the possibility of heat stress as well as complicating the underlying calculations (Orlov et al. 2020). However, there is potential to bring new data sets to bear on this challenge. One such example is the data base on piece rate contracts in the Central Valley of California used by Graff-Zivin and Neidell (2012) to assess the impacts of elevated air pollution on farm worker productivity. This would appear to be well-suited to evaluating the impact of heat stress on farm labor.

When it comes to assessing the impacts of climate on total factor productivity growth, the US data sets from USDA have already been well-exploited by Chambers and Pieralli (2020), Ortiz-Bobea et al. (2018) and Liang et al. (2017). However, there is a need for comparable studies outside the US. Towards this end, the OECD has established a Network on Agricultural Total Factor Productivity and the Environment: https://www.oecd.org/agriculture/topics/network-agricultural-productivity-and-environment/. This should serve as an important clearinghouse for future TFP data sets. A deeper issue, however, relates to identifying the impact of climate on the accumulation/depreciation of knowledge capital and its potential to generate TFP growth. This presents the greatest challenge due to the very long lag associated with this production process (up to 50 years in the US). Using a hierarchical Bayesian approach, Baldos et al. (2019) are able to estimate this lag structure and reconstruct the knowledge capital associated with public R&D in US agriculture using R&D spending data from 1900 to 2011, but they did not attempt to isolate the impact of climate on knowledge capital itself. Revisiting this work might be an appropriate starting point for exploratory work in this area. Unfortunately, other equally long time series on R&D spending are unlikely to be readily available for some time to come.

This broader view of climate impacts on agriculture also has important policy implications. Firstly, agricultural impacts are an important contributor to the social cost of carbon. Upward revision of these estimates can boost significantly the overall social cost of carbon (Moore et al., 2017a, 2017b). A higher social cost of carbon implies that more climate mitigation effort is justified. Furthermore, since much of the low cost greenhouse gas mitigation currently available is land-based, added mitigation effort bears directly on the spatial extent of farming on the planet (Smith et al. 2014). More mitigation will likely contribute to higher food prices, raising further concerns about food security and poverty (Hussein et al., 2013).

The prominence of heat stress on labor in the poorest countries of the world also suggests that current studies omitting this factor are greatly understating the economic and human impacts of climate change in the most vulnerable regions. Adaptation to such stresses will be challenging. New technology pathways for the agricultural sector, including not only plant breeding but also rapid mechanization of many farming activities will be required. These adaptations can be greatly facilitated by additional investments in research and development, in both the public and private sectors. Indeed, public–private collaboration will be essential to the development and dissemination of new technologies in the face of a warming planet.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2020.101954.

References

Aguiar, Angel, Narayanan, Badri, McDougall, Robert, 2016. An Overview of the GTAP 9 Data Base. J. Glob. Econom. Anal. 1 (1), 181–208. https://doi.org/10.21642/JGEA.010103AF.

Aguiar, Angel, Chepeliev, Maksym, Corong, Erwin L., McDougall, Robert, van der Mensbrugghe, Dominique, 2019. The GTAP data base: version 10. J. Glob. Econ. Anal. 4 (1), 1–27. https://doi.org/10.21642/JGEA.040101AF.

Alston, J.M., James, J.S., Andersen, M.A., Pardey, P.G., 2010. Research Lags and Spillovers. Persistence Pays 239–269.

Armington, Paul S., 1969. A Theory of Demand for Products Distinguished by Place of Production (Une Théorie de La Demande de Produits Différenciés d'après Leur Origine) (Una Teoría de La Demanda de Productos Distinguiéndolos Según El Lugar de Producción). Staff Papers (Int. Monetary Fund) 16 (1), 159–178. https://doi.org/10.2307/3866403.

Baldos, Uris Lantz C., Frederi G. Viens, Thomas W. Hertel, Keith O. Fuglie, 2019. R&D Spending, Knowledge Capital, and Agricultural Productivity Growth: A Bayesian Approach. Am. J. Agric. Econom. 101 (1), 291–310. http://doi.org/10.1093/ajae/aay039.

Bale, Jeffery S., Masters, Gregory J., Hodkinson, Ian D., Caroline Awmack, T., Bezemer, Martijn, Brown, Valerie K., Butterfield, Jennifer, et al., 2002. Herbivory in Global Climate Change Research: Direct Effects of Rising Temperature on Insect Herbivores. Glob. Change Biol. 8 (1), 1–16. https://doi.org/10.1046/j.1365-2486.2002.00451.x.

Ball, Eldon. 2006. Productivity and Output Growth in U.S. Agriculture. Agriculture Handbook EIB-16. Agricultural Resources and Environmental Indicators. Economic Research Service, U.S. Department of Agriculture.

Buzan, J.R., Oleson, K., Huber, M., 2015. Implementation and Comparison of a Suite of Heat Stress Metrics within the Community Land Model Version 4.5. Geosci. Model Develop. 8 (2), 151–170. https://doi.org/10.5194/gmd-8-151-2015.

Buzan, Jonathan, Huber, Matthew, 2020. Moist Heat Stress on a Hotter Earth. Annu. Rev. Earth Planet. Sci. 48, 1–30. https://doi.org/10.1146/annurev-earth- 053018-060100.

Cairns, J.E., Sonder, K., Zaidi, P.H., Verhulst, N., Mahuku, G., Babu, R., Nair, S.K., et al., 2012. Maize Production in a Changing Climate: Impacts, Adaptation, and Mitigation Strategies. In: Donald L. Sparks (Ed.). Advances in Agronomy, Advances in Agronomy. Academic Press. Vol. 114, pp. 1–58. http://doi.org/10.1016/B978-0-12-394275-3.00006-7.

Challinor, A.J., Watson, J., Lobell, D.B., Howden, S.M., Smith, D.R., Chhetri, N., 2014. A Meta-Analysis of Crop Yield under Climate Change and Adaptation. Nat. Clim. Change 4 (4), 287–291. https://doi.org/10.1038/nclimate2153.

Chambers, Robert G., Pieralli, Simone, 2020. The Sources of Measured US Agricultural Productivity Growth: Weather, Technological Change, and Adaptation. Am. J. Agric. Econ. 102 (4), 1198–1226. https://doi.org/10.1002/ajae.12090.

Corong, Erwin L., Hertel, Thomas W., McDougall, Robert, Tsigas, Marinos E., van der Mensbrugghe, Dominique, 2017. The Standard GTAP Model, Version 7. J. Glob. Econom. Anal. 2 (1), 1–119. https://doi.org/10.21642/JGEA.020101AF.

Diewert, W.E., 1981. The Comparative Statics of Industry Long-Run Equilibrium. Can. J. Econom./Revue Canadienne d'Economique 14 (1), 78–92.

Dunne, J.P., Stouffer, R.J., John, J.G., 2013. Reductions in labour capacity from heatstress under climate warming. Nat. Clim. Change 3, 563.

FAO. 1995. Dimensions of Need. 1995. http://www.fao.org/3/u8480e/U8480E00.htm#Dimensions%20of%20need.

Fischer, Anthony, Derek Byerlee, Greg edmeades, 2104. Crop Yields and Global Food Security: Will Yield Increase Conitinue to Feed the World? Canberra, Australia: ACIAR.

Fuglie, K., 2018. R&D Capital, R&D Spillovers, and Productivity Growth in World Agriculture. Appl. Econom. Perspect. Policy 40 (3), 421–444. https://doi.org/10.1093/aepp/ppx045.

Fuglie, Keith, Gautam, Madhur, Goyal, Aparajita, Maloney, William, 2020. Harvesting Prosperity. World Bank Publications, Washington D.C.

Gómez, Miguel I., Barrett, Christopher B., Raney, Terri, Pinstrup-Andersen, Per, Meerman, Janice, Croppenstedt, André, Carisma, Brian, Thompson, Brian, 2013. Post-Green Revolution Food Systems and the Triple Burden of Malnutrition. Food Policy 42 (October), 129–138. https://doi.org/10.1016/j.foodpol.2013.06.009.

Graff Zivin, Joshua, Matthew Neidell, 2012. The Impact of Pollution on Worker Productivity. American Econom. Rev. 102 (7), 3652–73. http://doi.org/10.1257/aer.102.7.3652.

Hannukkala, A.O., Kaukoranta, T., Lehtinen, A., Rahkonen, A., 2007. Late-Blight Epidemics on Potato in Finland, 1933–2002; Increased and Earlier Occurrence of Epidemics Associated with Climate Change and Lack of Rotation. Plant. Pathol. 56 (1), 167–176. https://doi.org/10.1111/j.1365-3059.2006.01451.x.

Haqiqi, Iman, Danielle S. Grogan, Thomas W. Hertel, Wolfram Schlenker, 2019. Predicting Crop Yields Using Soil Moisture and Heat: An Extension to Schlenker and Roberts (2009). 291093. 2019 Annual Meeting, July 21-23, Atlanta, Georgia. 2019 Annual Meeting, July 21-23, Atlanta, Georgia. Agricultural and Applied Economics Association. https://ideas.repec.org/p/ags/aaea19/291093.html.

Heal, G., Park, J., 2016. Temperature Stress and the Direct Impact of Climate Change: A Review of an Emerging Literature. Rev. Environ. Econom. Policy, August, rew007. http://doi.org/10.1093/reep/rew007.

Hertel, T.W., Baldos, U.L.C., van der Mensbrugghe, 2016. Predicting Long Term Food Demand, Cropland Use and Prices. Ann. Rev. Resour. Econom. 8, 417–441.

Hertel, T.W., Burke, M.B., Lobell, D.B., 2010. The Poverty Implications of Climate-Induced Crop Yield Changes by 2030. Global Environ. Change 20 (4), 577–585. https://doi.org/10.1016/j.gloenvcha.2010.07.001.

Huff, Karen, Thomas Hertel, 2001. Decomposing Welfare Changes in GTAP. GTAP Technical Paper No. 05. 2001. http://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=308.

Hussein, Zekarias, Hertel, T.W., Golub, Alla, 2013. Climate Change Mitigation Policies and Poverty in Developing Countries. Environ. Res. Lett. 8 (3), 035009. https://doi.org/10.1088/1748-9326/8/3/035009.

IPCC. 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Cambridge University Press, Cambridge, New York, NY.

Jagnani, Maulik, Barrett, Christopher B., Liu, Yanyan, You, Liangzhi, 2020. Within-Season Producer Response to Warmer Temperatures: Defensive Investments by Kenyan Farmers. Econom. J. Forthcoming. https://www.dropbox.com/s/cc7351pkk16yj7b/JBLY.pdf?dl=0.

Key, Nigel, Sneeringer, Stacy, 2014. Potential Effects of Climate Change on the Productivity of U.S. Dairies. Am. J. Agric. Econ. 96 (4), 1136–1156. https://doi.org/10.1093/ajae/aau002.

Kjellstrom, Tord, Briggs, David, Freyberg, Chris, Lemke, Bruno, Otto, Matthias, Hyatt, Olivia, 2016. Heat, Human Performance, and Occupational Health: A Key Issue for the Assessment of Global Climate Change Impacts. Annu. Rev. Public Health 37 (1), 97–112. https://doi.org/10.1146/annurev-publhealth-032315-021740.

Liang, Xin-Zhong, You Wu, Robert G. Chambers, Daniel L. Schmoldt, Wei Gao, Chaoshun Liu, Yan-An Liu, Chao Sun, Jennifer A. Kennedy, 2017. Determining Climate Effects on US Total Agricultural Productivity. Proc. Natl. Acad. Sci. 114 (12), E2285–92. http://doi.org10.1073/pnas.1615922114.

Lima, Cicero, Buzan, Jonathan, Moore, Frances, Baldos, Uris Lantz, Huber, Matthew, Hertel, Thomas W, 2020. Heat Stress on Agricultural Workers Exacerbates Crop Impacts of Climate Change. Review.

Lobell, David B, Asseng, Senthold, 2017. Comparing Estimates of Climate Change Impacts from Process-Based and Statistical Crop Models. Environ. Res. Lett. 12 (1), 015001. https://doi.org/10.1088/1748-9326/aa518a.

Mader, T.L., 2014. Animal Welfare Concerns for Cattle Exposed to Adverse Environmental Conditions. J. Anim. Sci. 92 (12), 5319–5324.

McCarl, Bruce A., Hertel, Thomas W., 2018. Climate Change as an Agricultural Economics Research Topic. Appl. Econom. Perspect. Policy 40 (1), 60–78. https://doi.org/10.1093/aepp/ppx052.

Minard, David, Belding, Harwood S., Kingston, James R., 1957. Prevention of Heat Casualties. J. Am. Med. Assoc. 165 (14), 1813–1818. https://doi.org/10.1001/jama.1957.02980320043010.

Moore, Frances, Baldos, U.L.C., Hertel, Thomas, 2017a. Economic Impacts of Climate Change on Agriculture: A Comparison of Process-Based and Statistical Yield Models. Environ. Res. Lett., April. https://doi.org/10.1088/1748-9326/aa6eb2.

Moore, Frances C, Baldos, U.L.C., Hertel, Thomas, Diaz, Delavane, 2017b. New Science of Climate Change Impacts on Agriculture Implies Higher Social Cost of Carbon. Nat. Commun. 8 (1), 1607.

Myers, Samuel S., Zanobetti, Antonella, Kloog, Itai, Huybers, Peter, Leakey, Andrew D.B., Bloom, Arnold, Carlisle, Eli, et al., 2014. Rising CO2 Threatens Human Nutrition. Nature 510 (7503), 139–142. https://doi.org/10.1038/nature13179.

Orlov, Anton, Sillmann, Jana, Aunan, Kristin, Kjellstrom, Tord, Aaheim, Asbjørn, 2020. Economic Costs of Heat-Induced Reductions in Worker Productivity Due to Global Warming. Global Environ. Change 63 (July), 102087. https://doi.org/10.1016/j.gloenvcha.2020.102087.

Ortiz-Bobea, Ariel, Knippenberg, Erwin, Chambers, Robert G., 2018. Growing Climatic Sensitivity of U.S. Agriculture Linked to Technological Change and Regional Specialization. Sci. Adv. 4 (12), eaat4343. https://doi.org/10.1126/sciadv.aat4343.

Parsons, Ken, 2006. Heat Stress Standard ISO 7243 and Its Global Application. Ind. Health 44 (3), 368–379. https://doi.org/10.2486/indhealth.44.368.

Robinson, Sherman, van Meijl, Hans, Willenbockel, Dirk, Valin, Hugo, Fujimori, Shinichiro, Masui, Toshihiko, Sands, Ron, et al., 2014. Comparing Supply-Side Specifications in Models of Global Agriculture and the Food System. Agric. Econom. 45 (1), 21–35. https://doi.org/10.1111/agec.12087.

Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., et al., 2013. The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and Pilot Studies. Agric. For. Meteorol. 170 (March), 166–182. https://doi.org/10.1016/j.agrformet.2012.09.011.

Schlenker, W., Roberts, M.J., 2009. Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change. Proc. Natl. Acad. Sci. 106 (37), 15594–15598. http://doi.org/10.1073/pnas.0906865106.

Sheahan, Megan, Barrett, Christopher B., Goldvale, Casey, 2017. Human Health and Pesticide Use in Sub-Saharan Africa. Agric. Econom. 48 (S1), 27–41. https://doi.org/10.1111/agec.12384.

Smith, Matthew R., Myers, Samuel S., 2018. Impact of Anthropogenic CO2 Emissions on Global Human Nutrition. Nat. Clim. Change 8 (9), 834–839. https://doi.org/10.1038/s41558-018-0253-3.

Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E.A., Haberl, H., et al. 2014. Agriculture, Forestry and Other Land Use (AFOLU). In: Chapter 11 in IPCC, 2014: Climate Change 2014: Mitigation of Climate Change. Cambridge Press, NY.

Stevens, Andrew, 2017. Temperature, Wages and Agricultural Labor Productivity. Job Market Paper. https://are.berkeley.edu/sites/default/files/job-candidates/paper/stevens_jmp_jan16.pdf.
USDA ERS. 2019. International Agricultural Productivity. On-line database. 2019. https://www.ers.usda.gov/data-products/international-agricultural-productivity/.
White, J.W., Hoogenboom, G., Kimball, B.A., Wall, G.W., 2011. Methodologies for Simulating Impacts of Climate Change on Crop Production. Field Crops Res. 124 (3), 357–368.
Zander, Kerstin K., Botzen, Wouter J.W., Oppermann, Elspeth, Kjellstrom, Tord, Garnett, Stephen T., 2015. Heat Stress Causes Substantial Labour Productivity Loss in Australia. Nat. Clim. Change 5 (7), 647–651. https://doi.org/10.1038/nclimate2623.
Zhang, Peng, Deschenes, Olivier, Meng, Kyle, Zhang, Junjie, 2018. Temperature Effects on Productivity and Factor Reallocation: Evidence from a Half Million Chinese Manufacturing Plants. J. Environ. Econom. Manage. 88 (March), 1–17. https://doi.org/10.1016/j.jeem.2017.11.001.
Ziska, Lewis H., Dana M. Blumenthal, G. Brett Runion, E. Raymond Hunt Jr., Hilda Diaz-Soltero, 2011. Invasive Species and Climate Change: An Agronomic Perspective. Clim. Change 105 (1–2), 13–42. http://doi.org/10.1007/s10584-010-9879-5.