



The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
<http://ageconsearch.umn.edu>
aesearch@umn.edu

Papers downloaded from AgEcon Search may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.



Global Trade Analysis Project
<https://www.gtap.agecon.purdue.edu/>

This paper is from the
GTAP Annual Conference on Global Economic Analysis
<https://www.gtap.agecon.purdue.edu/events/conferences/default.asp>

April 6, 2020

Climate Impacts on Agriculture: Searching for Keys under the Streetlight

By Thomas W. Hertel^{1,2,*}
and
Cicero Z. de Lima¹

*Corresponding author email: hertel@purdue.edu. The authors acknowledge valuable comments on an earlier draft by Christopher Barrett and Keith Fuglie. Hertel and Lima acknowledge funding from the U.S. Department of Energy, Office of Science, Biological and Environmental Research Program, Earth and Environmental Systems Modeling, MultiSector Dynamics, Contract No. DE-SC0016162. 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”.

¹Center for Global Trade Analysis, Purdue University

²Purdue Climate Change Research Center

42

43

44 **Climate Impacts on Agriculture: Searching for Keys under the Streetlight**

45

46

47 **Abstract**

48

49 This paper provides a critical assessment of the literature estimating the consequences of climate
50 impacts in agriculture and the food system. This literature focuses overwhelmingly on the impact
51 of elevated CO₂ concentrations in the atmosphere, higher temperatures and changing precipitation
52 on staple crop yields. While critically important for food security, we argue that researchers have
53 gravitated to measuring impacts ‘under the streetlight’ where data and models are plentiful. We
54 argue that prior work has largely neglected the vast majority of potential economic impacts of
55 climate change on agriculture. A broader view must extend the impacts analysis to inputs beyond
56 land, including the consequences of climate change for labor productivity, as well as the rate of
57 total factor productivity growth in the face of more rapidly depreciating knowledge capital. This
58 broader view must also focus more attention on non-staple crops, which, while less important from
59 a caloric point of view, are critically important in redressing current micronutrient deficiencies in
60 many diets around the world. The paper closes with numerical simulations that demonstrate the
61 extent to which limited input and output coverage of climate impacts can lead to considerable
62 underestimation of the consequences for food security and economic welfare – particularly in the
63 poorest regions of the world.

64

65

66 **Keywords:** Climate impacts, agriculture, heat stress, nutrition, productivity

67 **JEL code:** Q54

68

69

70 **1. Introduction and Knowledge Gaps**

71 All empirical research is opportunistic – at least to some degree. We tend to focus on topics for
72 which data and methods are readily available. There is a widely employed metaphor used to
73 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-lit section of sidewalk. When the man admits that he lost the keys in the park, the officer asks: 'So why aren't you looking

79 79 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
80 80 81 82 83 84 85 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.

86 The field of research where climate impact assessments have been most fully developed
87 pertains to the impacts of climate change on staple crops such as maize and wheat. It was natural
88 for crop modelers who had spent their career developing tools to guide management decisions in
89 wealthy, industrialized economies, typically in temperate climates, to turn to these models when
90 first asked to assess climate change challenges at global scale. Indeed, when White et al. (2011)
91 reviewed 221 studies of climate impacts on crops, they found that only a handful studies considered
92 the effects of elevated CO₂ on canopy temperature, and similarly few studies considered direct

93 heat effects on key crop developments. While these features were not central to management
94 decisions in the temperate environments where most of these crop models were developed, they
95 are critically important under future climate change – particularly in the tropics where elevated
96 temperatures already pose a challenge. This is problematic given the high degree of exposure and
97 vulnerability of the world's low-income populations currently living in the tropics. Fortunately,
98 through the efforts of AgMIP: the Agricultural Modeling Intercomparision Project (Rosenzweig
99 et al. 2013), there have been significant efforts to extend the validity of these crop models to
100 developing countries.

101 The vast majority of these climate impact analyses have focused on a few staple crops,
102 including maize, rice, soybeans and wheat. Yet staple grains and oilseeds account for only about
103 one-quarter of global agricultural output, measured in value terms. And, while these staple food
104 products are the predominant sources of caloric intake in the world (that is why they are called
105 staples), today's malnutrition challenges are much broader (Gómez et al. 2013), and the coverage
106 of climate impacts on crops providing critical micro-nutrients is relatively weak. Furthermore,
107 there is now evidence that climate change itself may reduce the micro-nutrient intensity of many
108 of the world's crops (Myers et al. 2014). In addition, analysis of climate impacts on livestock
109 production – a key source of protein globally – has been largely neglected (McCarl and Hertel
110 2018). In this paper, I will highlight just how important are these gaps in our knowledge of climate
111 impacts, calling for researchers to start looking for key impacts beyond the bright streetlights.

112 A decomposition of sources of output growth over the past half-century complied by
113 USDA/ERS (2019) highlights a critical dimension of food production which has received
114 relatively little attention from climate scientists, namely total factor productivity (TFP) growth.
115 TFP growth is typically attributed to one of two sources: economic reforms that result in improved

116 efficiency in the farm sector, and the accumulation of knowledge capital which, in turn, is
117 translated into innovations that improve farm productivity (Alston et al. 2010). Economic reforms
118 typically generate one-off gains, and so it is hardly surprising that the world has come to rely ever
119 more heavily on knowledge-driven TFP gains (Fuglie et al. 2020). However, the rate at which
120 knowledge capital is translated into TFP growth varies greatly across regions and is likely related
121 to the agro-climatic environment in which innovations are being undertaken (IPCC 2014). This is
122 a dimension of climate change that has received almost no attention to date by those seeking to
123 quantify climate impacts on food security. How will higher temperatures and more variable rainfall
124 affect the cost and success of future plant breeding?

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

135 **2. Analytical Framework**

136 In order to assess the relative importance of different factors driving food production, both at a
137 regional and global scale, we use the lens of an aggregate, agricultural production function:

138 $Y = Af(\mathbf{X})$ where Y is aggregate agricultural output, \mathbf{X} is a vector of inputs, and A is an index
 139 of Total Factor Productivity (TFP). In light of the fact that the agricultural sector is generally
 140 populated by a large number of producers, with relatively free entry and exit, we can use the result
 141 of Diewert (1981) to assert that the aggregate production function will exhibit constant returns to
 142 scale, regardless of the farm level technologies. Furthermore, assuming that farmers minimize
 143 costs, we can derive the following relationship between the change in individual agricultural
 144 inputs, X_i , expressed in percentage change form in lower case, x_i , and the percentage change in
 145 aggregate output, also in lower case, y . In addition to percentage changes in TFP (A in the
 146 production function), denoted with lower case a , we introduce the possibility of input-augmenting
 147 technological change, a_i :

$$148 \quad y = a + \sum_i \theta_i (x_i + a_i) \quad (1)$$

149 In equation (1), $\theta_i = W_i X_i / PY$ is the cost share of input i , W_i is the input price, and P is the price
 150 of output. This cost share reflects the marginal productivity of input i due to the assumption of cost
 151 minimization by individual farms since this implies that: $f_i(X) = W_i / P$. Within this framework,
 152 climate impacts will be introduced through the terms a and a_i capturing Hicks-neutral changes
 153 in total factor productivity and input-biased impacts that only affect the productivity of a specific
 154 input.

155 In addition to altering the production function directly through the technology terms,
 156 climate impacts can also alter relative prices. For example, a decline in seasonal precipitation may
 157 lead to a shortage of water locally, in turn, raises the price of water, W_i , thereby altering the cost

158 minimizing use of irrigation in farming. This endogenous response alters the marginal productivity
159 of water and, along with these changes, there is likely to be a change in the associated cost share,
160 θ_i . If the elasticity of substitution between water and other inputs is less than one ($\sigma < 1$), then
161 such an input price increase will increase the cost share of water, thereby rendering this an
162 economically more important input in the overall production of food. This, in turn, will place a
163 higher value on innovations which conserve water ($a_w > 0$). On the other hand, if existing
164 technologies allow for a high degree of substitution between water and other inputs, then the cost
165 share of water will fall when water becomes more scarce. In summary, there is an important
166 interplay between prices in the economy and the impacts of climate change on food production
167 that will arise endogenously as a function of climate change, or exogenously as a function of
168 broader economic developments as conveyed to farmers through changing prices.

169 To obtain an analytical expression for the partial equilibrium change in food output in the
170 face of climate change, we must augment this simple model of agricultural production in several
171 ways. First of all, we add a downward sloping farm level demand curve for food, with elasticity
172 $-\eta_D$. To reflect supply constraints, we add an upward sloping supply schedule for the land/water
173 composite (simply call this land, denoted L for the sake of convenience) with land rental supply
174 elasticity ν_L . Next, we assume that capital, labor and intermediate inputs are in perfectly elastic
175 supply over the long run (i.e., their input prices are dictated by the non-farm economy). Finally,
176 we must specify precisely how the system is affected by climate change, i.e., which technology
177 terms in (1) will be shocked: a or some combination of the a_i variables.

178 The most popular representation of climate change in equilibrium models of agriculture
179 (Robinson et al. 2014) involves shocking a_L with the size of the shock dictated by biophysical

180 models' predictions of the change in yield as we move from current to future climate (see also
181 summary in Table 1 in Hertel, Baldos, and van der Mensbrugghe 2016). The logic is that, if these
182 crop models predict (e.g.) a 10% decline in yields under future climate, then that means that land
183 will be 10% less productive. However, if none of the other a_i variables are perturbed, then these
184 other inputs will remain as productive as before. This opens the possibility of substituting those
185 inputs for land, the effective price of which (W_L / A_L) has risen. This characterization of climate
186 change gives rise to the following equilibrium change in output (Hertel, Baldos, and van der
187 Mensbrugghe 2016):

188
$$y = (1 + \nu_L) \eta_D a_L / \eta \quad (2)$$

189 Where $\eta = \eta_D + \eta_S$ is the aggregate price responsiveness in the market (i.e., the sum of supply and
190 demand elasticities). The two terms in the numerator of (2) capture the direct impact on output of
191 the shift in land supply $\eta_D a_L / \eta$ and the indirect effect through the impact of climate change on
192 land rents and therefore on cropland use (hence the presence of the land supply elasticity:
193 $\nu_L \eta_D a_L / \eta$). Clearly, if the biophysical models predict a future decline in yields, $a_L < 0$, output
194 will fall. It will fall more, the more price sensitive is the farm level demand for food, and the more
195 responsive is the land supply to agricultural returns.

196 **3. Which inputs are affected by climate change?**

197 *Cost Shares as a Key Metric:* As noted above, most of the existing literature has focused on
198 changes in crop output per unit of land (i.e., crop yields) when characterizing climate impacts in
199 agriculture. Before going further let us pause to think about the relative economic importance of
200 land—the one input which has commanded the most attention from previous authors. With

201 equation (1) in mind, the most natural way to undertake such a comparison across diverse inputs
 202 is through the relative size of the cost shares, θ_i . Estimates of cost shares may be obtained from
 203 econometric studies of agricultural production. These studies recognize that farms' choices of
 204 input intensities are endogenous and a function of relative prices. Furthermore, in any given year,
 205 there are many stochastic factors operating on the observed input costs (Ball 2006). The GTAP
 206 data base (Aguiar et al., 2019) reports national agricultural cost shares wherein the composition of
 207 national-level value-added is obtained regional econometric studies. Figure 1 summarizes these
 208 cost shares aggregated to the level of the entire world, as well as for two very different regions:
 209 United States (USA) and Sub-Saharan Africa (SSA).

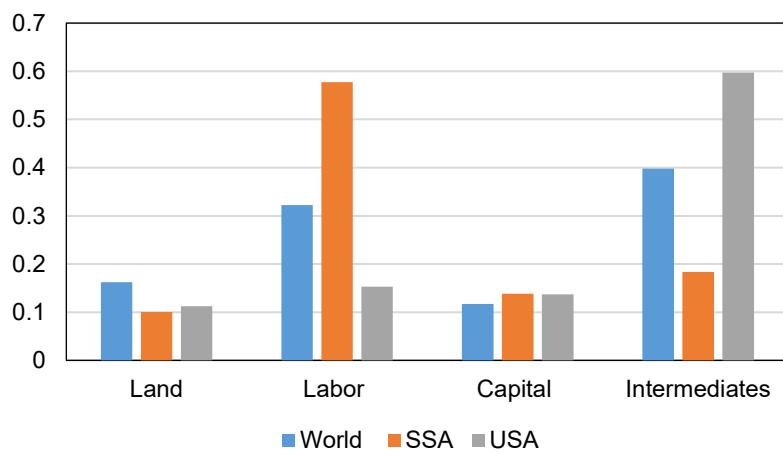


Figure 1. Shares of inputs in total costs for agriculture, for select regions. Source: GTAP v.10 data base, Aguiar et al., 2019.

219

220 There are several remarkable things about the estimates of agricultural cost shares shown
 221 in Figure 1. First is the enormous difference in the share of intermediate inputs, and, by subtraction,
 222 the share of value-added in total costs. In the US, value-added (land, labor and capital) accounts
 223 for only 40% of input costs whereas in the SSA region, this share is more than 80%. Within the
 224 value-added composite, labor is dominant in the SSA region, followed by capital¹ and land. This

¹ 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

225 suggests that anything that alters the productivity of labor in the region (e.g., heat stress) could
226 have a dramatic impact on agricultural output. And if the heat stress impact in SSA is larger than
227 in other regions, this will be magnified by the large labor cost share in that region. In the US,
228 capital and labor exhibit comparable cost shares. In both regions, land is the least important input
229 from the cost share point of view. (Although globally, land's cost share is larger than that of the
230 capital input.) The modest economic importance of the land input will be somewhat surprising to
231 those who are used to thinking of agricultural production as being largely driven by land. However,
232 the declining relative importance of agricultural land in the economy was first highlighted more
233 than 60 years ago by Nobel Laureate T.W. Schultz (1953). He emphasized the increasing
234 importance of other inputs, in particular, skilled labor, capital and knowledge (in the form of new
235 technologies). Indeed, the role of technological improvements in promoting agricultural
236 production is a theme which will be explored in some depth below.

237 *Climate Impacts as TFP Changes:* An important conceptual question has to do with how
238 we interpret the climate impact results emerging from biophysical models of crop production. As
239 noted above, the predominant approach has been one in which the changes in yields predicted by
240 crop models are treated as a perturbation to the productivity of land (a_L), leading to the long run
241 equilibrium change in output reported in equation (2). But others have challenged this, suggesting
242 a different thought experiment for incorporating the climate induced yield impacts into equation
243 (1) (Hertel, Burke, and Lobell 2010). For example, consider the case where, if the farmer engaged
244 in exactly the same activities under the new climate (i.e., no climate-induced input substitution),

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.

245 then yields would be 10% lower. If both the land and the non-land input levels are unaltered in this
246 thought experiment, then the output reduction of 10% is equivalent to a decline in a_i for *all the*
247 *inputs* in equation (1). This, in turn, is equivalent to a Hicks-neutral productivity shock of -10%,
248 i.e., $a = -10$. As we will see, this subtle difference in translation of the agronomic results into
249 economic consequences has dramatically different food security implications.

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

$$253 \quad y = (1 + \eta_s) \eta_D a / \eta \quad (3)$$

254 Where the elasticity of commodity supply is the sum of the extensive and intensive margins of
255 supply response: $\eta_s = \theta_L^{-1} \nu_L + \sigma(\theta_L^{-1} - 1)$. In this expression θ_L^{-1} is the inverse of the cost share of
256 land and σ is the elasticity of substitution between land and other inputs governing the scope for
257 intensification (or de-intensification) of agricultural production. Comparing (3) and (2) we see
258 that, even ignoring the possibility of variable input substitution for land (assuming $\sigma = 0$), the
259 inverse cost share applied to the land supply elasticity, ν_L , will sharply magnify the impact of this
260 climate shock on agricultural output. For example, taking the USA cost share of land from Figure
261 1 as roughly 0.10, *this implies a ten-fold magnification effect* when the yield shock is interpreted
262 as a perturbation to TFP.

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

265
$$p + a = \sum_i \theta_i (w_i - a_i) \quad (4)$$

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

277 *Heat Stress and Labor Capacity in Agriculture:* Beyond the agronomic assessments of
278 climate impacts on plant growth, there is now mounting evidence that global warming will sharply
279 reduce labor capacity – particularly when workers are outdoors and exposed to solar radiation.
280 Research in this area has been advancing recently and is summarized in the *Annual Reviews* paper
281 by Buzan and Huber (2020). Those authors emphasize the importance of considering the
282 combination of heat and humidity as presenting a significant threat to human's ability to function,
283 since, in the presence of high humidity, the human body has great difficulty releasing internally
284 generated heat. The US military developed a metric to address the risk posed to personnel from
285 prolonged exposure to the combination of high heat and humidity (Minard, Belding, and Kingston
286 1957). It is called Wet Bulb Globe Temperature (WBGT) and has also been adopted by the

287 International Standardization Organization (ISO) to measure workplace heat stress (Parsons 2006).
288 While WBGT has not been computed at global scale based on climate model outputs, a simplified
289 version of this measure (sWBGT) has been incorporated into climate models (J. R. Buzan, Oleson,
290 and Huber 2015).

291 Buzan and Huber (2020) use the sWBGT measure, in combination with the Dunne et al.
292 (2013) equation for determining labor capacity, to compute global gridded labor capacity in their
293 end of 20th century baseline (deemed to be current climate) as well as for a world in which there is
294 an average of +4 degrees C global warming. In their baseline, current global annual (population-
295 weighted) labor capacity is estimated to be 80% with regional averages varying from 98% in the
296 high latitudes (i.e., almost no constraints) to 71% in the tropics (significant capacity limitations
297 under current climate). At +4 degrees C, the global average drops to 59%, with labor capacity in
298 the tropics falling to 40%. This is a dramatic shock to the productivity of labor and it is indicative
299 of the kinds of productivity losses that are likely to occur on non-mechanized farms where workers
300 are exposed to direct solar radiation. Even in the US, where agriculture is highly mechanized –
301 particularly for row crops, the impact on workers cultivating and harvesting specialty crops has
302 been shown to be significant (Stevens 2017).

303 Lima et al. (Lima et al. 2020) incorporate the combination of sWBGT estimates from a
304 suite of climate models into the GTAP model of global trade and production. In terms of equation
305 (1), these are treated as shocks to a_i , i.e., partial factor productivity losses applied to labor. The
306 authors proceed to compare the welfare cost of these labor capacity losses to the losses based on a
307 meta-analysis of IPCC studies of crop yield losses (Moore et al., 2018). Importantly, in that prior
308 study, the yield losses were treated as total factor productivity shocks (perturbations to α). Even

309 with this aggressive interpretation of crop yield impacts, Lima et al. (2020) find that global welfare
310 losses at +3C were comparable between the two scenarios (α_i shocks to labor capacity vs. α
311 shocks to crop productivity). Furthermore, they find that the distribution of losses from these two
312 sets of climate impacts are quite different, with the labor capacity losses concentrated in Southeast
313 Asia, South Asia and Sub Saharan Africa. In short, ignoring the impacts of combined heat and
314 humidity on labor capacity paints a very distorted picture of how climate change affects
315 agriculture. And, it greatly understates the adverse impacts in some of the world's poorest
316 countries.

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

326 Changes in agroecological conditions also elicit adaptation responses from producers
327 which can affect the mix of inputs employed as well as agricultural productivity. In a recent study
328 of maize producers in Kenya, Jagnani et al. (Jagnani et al. 2020) find that, when confronted with
329 warmer than normal temperatures during critical growing periods, farm households increase the
330 application of pesticides (often at the expense of fertilizer) as well as increasing the use of labor
331 for weeding. In addition to the increase in direct labor requirement, there is likely to be an further

332 burden on labor due to the adverse health impacts of increased pesticide use (Sheahan, Barrett, and
333 Goldvale 2017). In terms of the analytical framework laid out above, the effects of climate change
334 on the Kenyan maize farms may be viewed as a new technology that is both labor- and pesticide
335 using ($a_i < 0$) and therefore a drag on farm output growth.

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

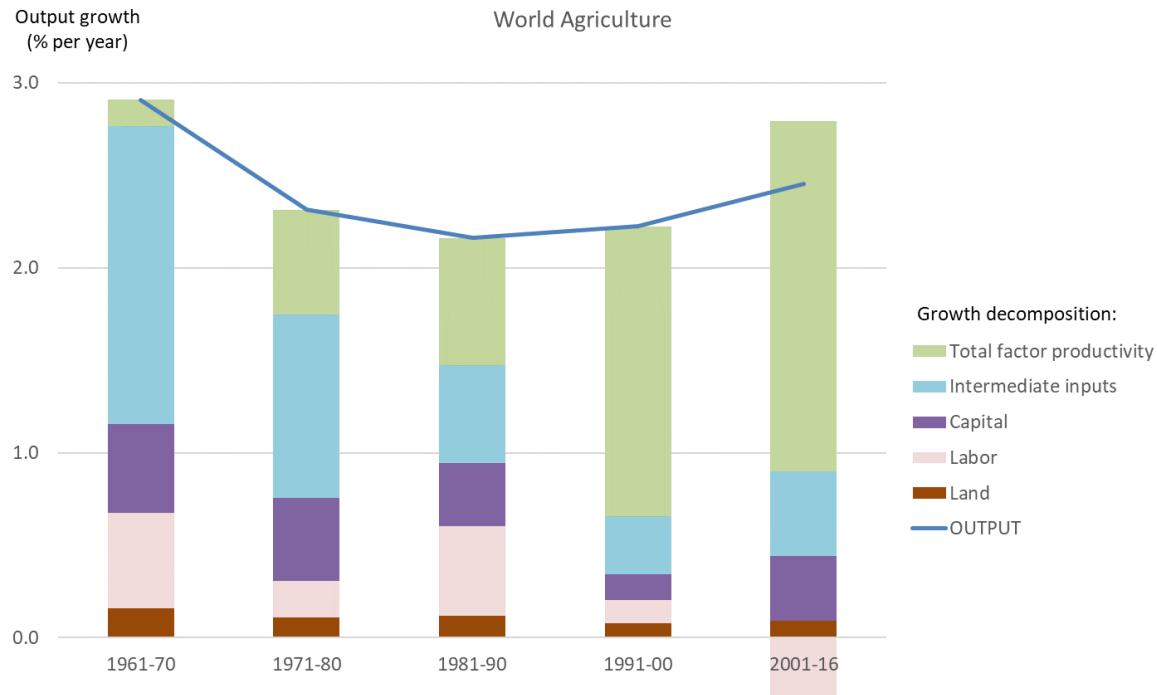
343 There is also little evidence available about how the productivity of intermediate inputs
344 will be affected by climate change. In the richest economies, where there is significant R&D
345 capacity and a well-developed private sector supply chain for delivering modern inputs to farmers,
346 there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

351 While labor and land may become less productive under climate change, irrigation water
352 is an input for which the marginal value product may actually rise. This could help offset some of
353 the other, adverse impacts of a warming climate. Haqiqi et al. (2019) estimate the marginal value

354 product of additional soil moisture (via irrigation) in corn production and find that this depends on
355 the initial state of soil moisture as well as commodity prices. In a season with high heat and low
356 rainfall, as well as elevated commodity prices, the value of applying additional irrigation water
357 can be very high. Provided supplemental irrigation water can be obtained, it can play an important
358 role in mitigating yield losses (Schlenker and Roberts 2009).

359 **4. Knowledge Capital**

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



372

373 Figure 2. Sources of global agricultural output growth, by decade, 1961-2016. Source: USDA-
374 ERS (2019).

375

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

380
$$A = A_O R_O^{\delta_O} R_S^{\delta_S} \quad (5)$$

381 where initial productivity, A_O , is enhanced by growth in the stock of own-research capital, R_O ,
382 and spill-in research capital, R_S with the elasticities δ_O and δ_S governing the responsiveness of

383 TFP to these investments. He surveys the literature aimed at estimating these elasticities, on a
384 region-specific basis, and uses these empirical estimates, along with equation (5), to provide an
385 attribution of TFP growth, by region, to knowledge capital. In so doing, he assumes a specific lag
386 structure through which the impact of knowledge capital rises through time, peaks, and then
387 declines as the value of this knowledge depreciates. The lag between R&D spending and TFP
388 growth can be very long. For example, Baldos et al. (2019) estimate that, in the United States, over
389 the course of the 20th century, the productivity impact of public R&D investments in agriculture
390 did not peak until 22 years following the initial investment. And the knowledge capital depreciated
391 relatively slowly over this period, with lingering impacts in the fifth decade after the money was
392 spent. (Not surprisingly, this closely mirrors the career profile of scientist!) Using this framework,
393 Fuglie (2018) is able to explain a large share of the TFP growth between 1990 and 2011 in the
394 OECD countries as well as Latin America and South Asia. (In other regions, such as China,
395 economic reforms also played a key role in boosting TFP.)

396 Given the dominant role of TFP in agricultural growth, a central question becomes: How
397 will climate change affect the future rate of TFP growth? Within this framework, there are two
398 distinct pathways for such impacts to be felt. First of all, climate change could accelerate the rate
399 of depreciation of existing knowledge capital – thereby depleting the stocks on the right hand side
400 of equation (5). This, in turn, will slow future TFP growth. The second channel is through the
401 elasticities in equation (5). Based on Fuglie's (2018) survey of the literature, there is tremendous
402 variation in these elasticities across regions – ranging from 0.07 for public R&D spending in
403 developing countries to figures in excess of 0.30 in the US. Surely much of this variation can be
404 explained by infrastructure, proximity to top research scientists and institutional stability and
405 governance. But agro-climatic conditions in some regions are likely to pose more significant

406 challenges than others. In the tropics, temperatures are already close to, or perhaps beyond, their
407 agronomic ideal. Increasing this threshold via tolerance to heat stress is likely to prove more
408 challenging than other measures aimed at boosting yields (Fischer, Byerlee, and Edmeades 2014).
409 Therefore, it seems reasonable that climate change might reduce these elasticities, thereby slowing
410 future TFP growth, for any given knowledge capital pathway.

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

428

429 **5. Product coverage**

430 Closely related to the issue of geographic coverage is the question of product coverage. The FAO
431 identifies 175 distinct crops, yet the vast majority of research on climate impacts in agriculture has
432 been undertaken on just 4 crops – the main staples: maize, wheat, rice and soybeans. Indeed, of
433 the 1782 climate impact yield estimates (from 94 independent studies) reported to the IPCC for
434 the AR5, these four crops accounted for 1165 of the total (74 of the 94 studies) (Challinor et al.
435 2014). And the remaining studies were so thinly spread that a statistical meta-analysis of climate
436 impacts was not possible beyond these four major crops (Moore et al., 2018). From a caloric point
437 of view, these four crops are also indeed dominant, accounting for nearly two-thirds of global
438 caloric consumption (FAO 1995). However, from a broader nutritional point of view, other crops
439 which are rich in micro-nutrients – particularly fruits and vegetables, as well as livestock products
440 which bring much needed protein to the diets of the poor -- are increasingly important and these
441 are largely missing from the climate impacts literature.

442 Analogously to the input aggregation above, the proper economic metric for aggregation
443 and comparison of outputs is that of revenue shares (assuming revenue maximization on multi-
444 product farms). Figure 3 provides data analogous to that in Figure 1, but now reporting output
445 revenue shares for agriculture. Each bar in the figure reports the share of total agricultural revenue
446 accounted for by a given product category, by region. We can see that, accounting for about one
447 quarter of global agricultural sales, the grains and oilseeds (staples) sector is hardly dominant.
448 Indeed, other crops are more significant, accounting for nearly one-third of global farm output.
449 And the global value of livestock output is even higher. Furthermore, livestock are susceptible to
450 heat and humidity in the same way as humans. Heat stress reduces feed intake and results in

451 diminished productivity (Key and Sneeringer 2014). Clearly the dominant focus on grains and
452 oilseeds in the climate impacts literature reflects a serious imbalance.

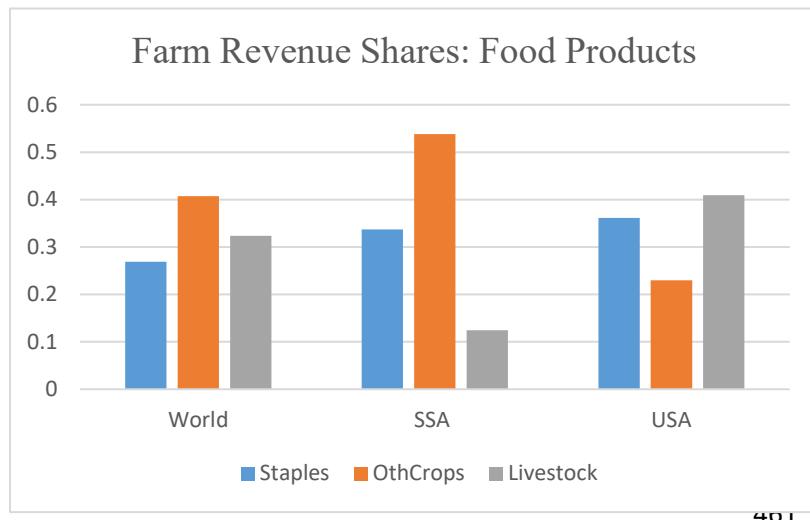


Figure 3. Share of food product categories in global agricultural sales: Source, GTAP 10 data base, Aguiar et al., 2019.

462 6. Climate Impacts on Nutrition

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

475 **7. Computational Illustrations**

476 We conclude this discussion of climate impacts on agriculture with a set of global economic
477 simulations, drawing on the previous work of Moore et al. (2017) and Lima et al. (2020). Those
478 authors have documented the impact of climate driven shocks to crop yields as well as climate
479 driven shocks to labor productivity. Here, we draw on their models and climate-induced
480 productivity shocks to illustrate the issues raised in the foregoing discussion. Both sets of authors
481 used the version 7 GTAP model and version 9 GTAP data base (Aguiar, Narayanan, and
482 McDougall 2016; Corong et al. 2017) to assess the impacts of climate change on production,
483 consumption, trade and welfare. Individual sectors in the standard GTAP model have the same
484 structure as the analytical partial equilibrium model detailed in equations (1) – (4). However, since
485 GTAP is a general equilibrium model, the farm-level demand elasticity in any given region is a
486 function of both domestic and foreign demands (including intermediate as well as final
487 consumption) as well as supply response in the rest of the world. I.e., when viewed from a regional
488 perspective, this demand response is now an excess demand elasticity – referring to the excess of
489 rest of world demand, over and above their own supplies. And the supply of non-land factors of
490 production is constrained by national market clearing conditions in this general equilibrium model
491 so that their prices are now endogenous.

492 *Experimental Design:* Table 1 provides the design for our four computational experiments.
493 They involve varying commodity coverage of the impacts (staples vs. all crops), as well as varying
494 the type of productivity shock (partial factor productivity impacts on land or labor, as in equation
495 (2) vs. total factor productivity impacts as in equation (3)). From Moore et al. (2017), we have
496 meta-analysis-based estimates of the impacts of climate change on staple crop yields for various

497 levels of global warming. (As noted previously, there are insufficient data points for the other
 498 171 FAO crops to allow for a meta-analysis outside of these staple crops.) Here, we focus on
 499 warming of +3C and utilize the authors' median estimates of yield impacts. The labor impacts are
 500 estimated following the methodology outlined in Lima et al. (2020), using the combination of the
 501 sWBGT measure of heat and humidity and the NIOSH method for estimating human labor
 502 capacity.

Table 1. Experimental Design

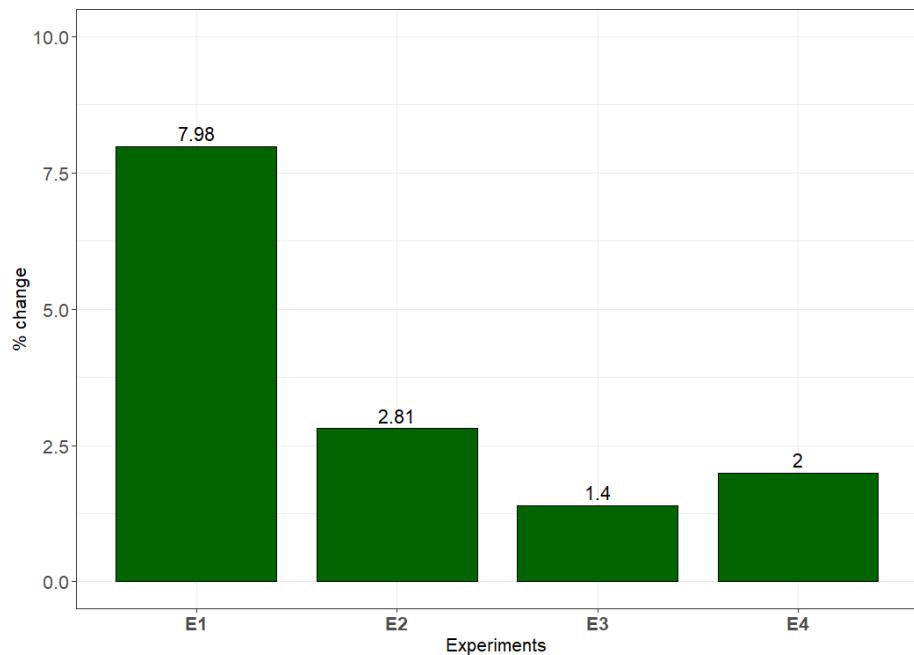
Product Coverage	Input Coverage		
	All	Land	Labor
Staples	E1	E2	E3
All Crops			E4

Comparing experiments E1 and E2 in Table 1 allows for a comparison of the all-input coverage with the land-only impacts approach to modeling

506 yield impacts. Contrasting the labor and land partial factor productivity shocks (E2 and E3) allows
 507 us to explore in greater detail the relative importance of these two types of climate impacts. While
 508 we don't have yield impact estimates for other crops or for livestock, we can explore the
 509 consequences of expanding product coverage in the case of labor productivity shocks, and for this,
 510 we contrast experiments E3 and E4.

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

518 The impact on staple food prices of the partial factor productivity labor shock, due to heat
519 stress limiting human's capacity to work, is even more modest than the shock to land productivity
520 (E3 vs. E2). Furthermore, expansion of the labor shocks to other crops sectors in E4, while boosting
521 the staples price impact somewhat, still does not reach the level of the partial factor land shock.
522 The fact that there is such a large difference in the staple food price effects of the two rival
523 interpretations of agronomic yield change estimates (E1 vs. E2) is a cause for great concern, as
524 there has been almost no discussion of these competing approaches.



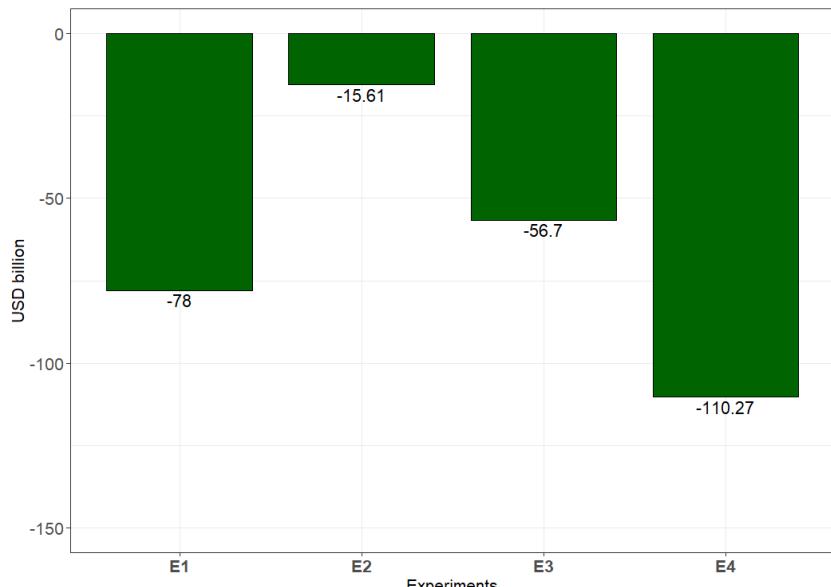
525

526 Figure 4. Impact of climate change experiments on the composite price of staple grains and
527 oilseeds. E1: Staple-TFP; E2: Staple-Land; E3: Staple-Labor; E4: All-Crops-Labor. Source:
528 Authors calculations.

529 *Aggregate welfare effects:* The cross-experiment comparison is quite different when we
530 focus on global welfare impacts (Figure 5). Here, we see that the global welfare loss suffered
531 when yields reduce TFP is far greater than that when only land productivity is affected.

532 However, when we compare the welfare loss from partial factor productivity reductions for land
533 only, vs. labor only, the latter is now dominant. Furthermore, in the case of welfare impacts, as
534 the extent of labor productivity losses broadens from staples to all crops, the losses increase
535 sharply. This makes sense, since, unlike the staples price index, welfare is an economywide
536 measure, so the more sectors are affected, the larger the impact.

537



538

539 Figure 5. Impact of climate change experiments on global welfare. E1: Staple-TFP; E2: Staple-
540 Land; E3: Staple-Labor; E4: All-Crops-Labor. Source: Authors calculations.

541 To gain deeper insight into these results, we turn to equation (6) which provides an
542 analytical decomposition of regional welfare changes in general equilibrium, measured as
543 Equivalent Variation for a given region s (EV^s). (See Huff and Hertel (2001) for the derivation
544 of this expression.) The climate change induced productivity shocks (in percentage change) are
545 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
546 factor productivity shocks to input j employed in sector i in region s . The first term in this

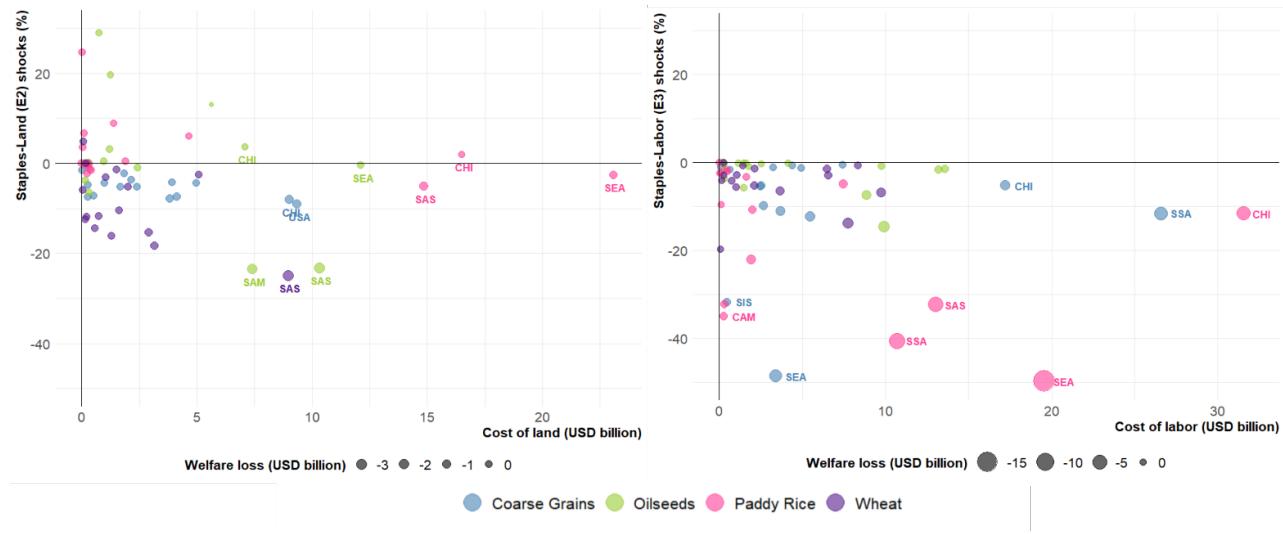
547 expression states that, if farmers plant the same crop using the same mix of inputs at mid-
 548 century, but harvest 1% less output, then the direct economic loss is equal to 1% of the value of
 549 output ($P^{is} Y^{is}$) of commodity i in region s . The second term in (6) captures the impact of the
 550 partial factor productivity shocks. Here, a 1% loss in (e.g.) labor capacity induces a direct
 551 welfare loss which is valued at 1% of the cost of labor employed in that sector ($W_j^{is} X_j^{is}$). These
 552 first two terms comprise the direct (first-order) welfare impacts of climate change. To translate
 553 these dollar changes into welfare terms, they must be multiplied by the EV scaling factor, (ψ_s),
 554 which is itself a function of the elasticity of expenditure with respect to utility.

$$555 \quad EV^s = (\psi^s) \left\{ \begin{array}{l} \sum_{i=1}^N (P^{is} Y^{is} (a^{is} / 100)) \\ + \sum_{i=1}^N \sum_{j=1}^M (W_j^{is} X_j^{is} (a_j^{is} / 100)) \\ + \sum_{i=1}^N (\tau^{is} P^{is} dY^{is}) \\ + \sum_{i=1}^N \sum_{r=1}^R (E^{isr} dPFOB^{isr}) \\ - \sum_{i=1}^N \sum_{r=1}^R (M^{irs} dPCIF^{irs}) \end{array} \right\} \quad (6)$$

556 Since the cost shares of labor and land are less than one, $\theta_i = W_i X_i / PY < 1$, it is hardly
 557 surprising that the aggregate welfare impacts of the partial factor productivity shocks are only a
 558 fraction of the TFP-driven welfare impacts. Somewhat more surprising, in light of the fact that
 559 the global cost shares of labor and land are quite similar (recall Figure 1), is the much larger
 560 welfare impact from the labor vs. land partial factor productivity shocks. Deeper investigation
 561 into the source of this discrepancy reveals that, while the agronomic-based yield shocks are quite
 562 variable, depending on the crop, climate and location, the labor capacity reductions are uniformly
 563 negative (Figure 6). Furthermore, the labor losses are greatest, precisely in those regions where

564 labor cost shares are relatively high, particularly rice production in Asia (Figure 6). The other
 565 point that emerges from Figure 6 is that in the most heat/humidity stressed regions of the world,
 566 where labor capacity losses are largest, the plants seem to fare better than the people under
 567 warming. This is particularly true for rice production in Asia where the yield impacts are modest
 568 – rice has a high optimal growing temperature – but the labor impacts are quite significant.

569



570

571 Figure 6. Cost of climate-affected agricultural inputs used in staple crops production. Land (E2:
 572 left hand panel) and Labor (E3: right hand panel) are each plotted against the shock to partial
 573 factor productivity of land and labor, respectively. The size of the circle denotes the welfare loss
 574 associated with each crop/input/region combination. Crop losses are color-coded by sector.

575 To investigate the plants vs. people impacts more fully we turn to Figure 7 which reports the
 576 impacts on output by region for rice and wheat. Rice is relatively well-adapted to warm, humid
 577 climates, with a high agronomic optimal temperature. Estimated yield losses under global warming
 578 are concentrated in South and Southeast Asia, while Europe, Japan, South America and Australia
 579 are projected to experience higher yields under +3C warming. And this is reflected in the output

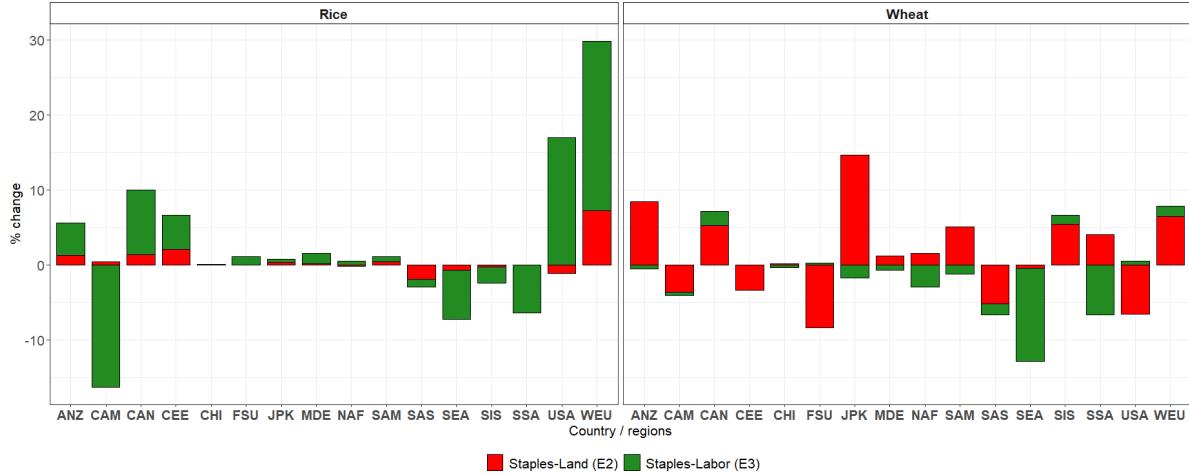
580 changes for rice, by region, in the top panel of Figure 7. This contrasts sharply with the labor
581 impacts. While rice thrives in a warm, humid environment, the combination of heat and humidity
582 is deadly for humans who can no longer dissipate their internally generated body heat under such
583 conditions. Thus, the impacts of climate change on rice production through the labor input are
584 much larger than that through the agronomic channels. Despite the fact that all regions of the world
585 experience diminished labor productivity in rice production, those experiencing the more modest
586 impacts (North America, Europe, Australia) increase rice production in order to make up for the
587 large declines in rice output in Central America, Asia and Africa.

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

594

595

596



597

598 Figure 7. Impacts of land (E2) vs. labor (E3) climate impacts on the pattern of staple crops
 599 output: Rice (left panel) and Wheat (right panel).

600

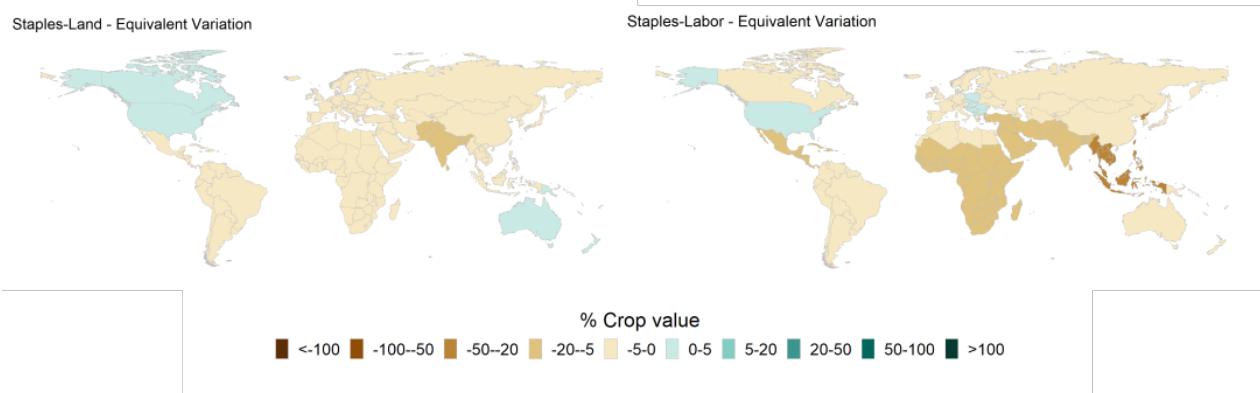
601 The remaining terms in equation (6) are the result of indirect (second-order) effects flowing
 602 from changes in equilibrium quantities and prices in the wake of direct climate impacts. The
 603 third term in (6) captures the interplay between climate change impacts and government policies.

604 For example, if the climate impacts cause shrinkage in a sector ($dY^{is} < 0$) that is subsidized (
 605 $\tau^{is} < 0$), then there will be an efficiency gain in general equilibrium, as resources are re-allocated
 606 to higher value uses ($\tau^{is} P^{is} dY^{is} > 0$). (In the GTAP model, this allocative efficiency effect
 607 comprises thousands of terms, reflecting the plethora of existing distortions in the economy – not
 608 just those related to output taxes or subsidies.)

609 The final two terms in (6) refer to the terms of trade effects on regional welfare. The most
 610 hard-hit regions under climate change will reduce production, which, in turn, will cause their
 611 prices to rise, relative to the world average. (This model reflects the fact that agricultural
 612 products are not homogeneous. Rather they are differentiated – in this case by region of origin,

613 as first pointed out by Armington (1969).) With export prices rising, relative to import prices,
614 those hard-hit regions ($dPFOB^{isr} > dCIF^{isr}$) which are significant net exporters of climate-
615 impacted commodities ($E^{is} >> M^{is}$), are expected to see large terms of trade gains. However,
616 since this component of the welfare change simply amounts to income transfers amongst regions,
617 when summed over all regions in the world, this effect washes out and therefore has no influence
618 in the global welfare impacts reported in Figure 5. Overall, the direct effect of climate change
619 accounts for about 90 percent of the global welfare change in all of our experiments, with the
620 allocative efficiency effects accounting for the remainder (roughly 10 percent of the global
621 welfare impact).

622 Figure 8 reports the geographic distribution of the full regional welfare impacts (i.e.,
623 considering all of the terms in equation (6)) stemming from the land and labor partial factor
624 productivity shocks to staple crops (E2 and E3). Contrasting the two panels, we see that the losses
625 in Southeast Asia and Sub-Saharan Africa stand out when labor capacity reductions are taken into
626 account. Central America and the Middle East also contribute significantly to the global welfare
627 losses under the labor stress experiment. In the labor stress experiment (E3), the benefitting regions
628 are fewer, and these gains are driven by improvements in the regions' terms of trade, not by
629 productivity gains, in contrast to the yield-based experiment (E2).



630

631 Figure 8. Impact of climate change experiments E2 and E3 on the regional welfare. Changes are
 632 relative to the 2011 baseline. The maps show the total welfare changes reported as equivalent
 633 variation for Staples-Land and Staples-Labor experiments. Welfare changes are normalized by the
 634 value of crop production of all staple crops. Source: Authors' calculations

635

636 **8. Discussion and Conclusions**

637 The purpose of this paper is not to provide comprehensive new estimates of the food price and
 638 welfare impacts of climate change in agriculture, but rather to highlight the extent to which those
 639 of us in the climate impacts community have been effectively 'looking for our keys under the
 640 streetlight'. The majority of the research to date on climate impacts in agriculture has focused
 641 solely on four staple crops, accounting for only about one-quarter of the total value of agricultural
 642 output. Furthermore, when it comes to assessing these impacts, the sole focus has been the
 643 productivity of the cropland input employed in farming, which itself accounts for only about 16%
 644 of total production costs. Viewed from the entirety of the global agricultural sector, this means
 645 researchers have been focusing on only 4% (.25 * 0.16 * 100%) of the economic value of global
 646 farming. What about the other 96%? This paper offers some evidence of significant impacts

647 outside of the staple plant domain. In particular, the workers employed in agriculture are likely to
648 be adversely affected by a warmer, more humid climate, and, in some regions, these impacts are
649 much larger than the impacts on the plants themselves. It is time to move beyond assessing yield
650 impacts for staple commodities where we have the best models and data, and venture into the realm
651 of other food products as well as other farm inputs and nutritional impacts.

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

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

669 dynamic impact on food output, resulting in higher food prices and reduced real incomes by mid-
670 century.

671 This broader view of climate impacts on agriculture also has important policy implications.
672 Firstly, agricultural impacts are an important contributor to the social cost of carbon. Upward
673 revision of these estimates can boost significantly the overall social cost of carbon (Moore et al.
674 2017). A higher social cost of carbon implies that more climate mitigation effort is justified.
675 Furthermore, since much of the low cost greenhouse gas mitigation currently available is land-
676 based and relates directly to the spatial extent of farming on the planet (Smith et al. 2014). More
677 mitigation will likely contribute to higher food prices, raising further concerns about food security
678 and poverty (Hussein, Hertel, and Golub 2013)

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

687

688

689

690

691 **References**

692

693 Aguiar, Angel, Badri Narayanan, and Robert McDougall. 2016. “An Overview of the GTAP 9
694 Data Base.” *Journal of Global Economic Analysis* 1 (1): 181–208.
695 <https://doi.org/10.21642/JGEA.010103AF>.

696 Alston, J.M., J.S. James, M.A. Andersen, and P.G. Pardey. 2010. “Research Lags and
697 Spillovers.” *Persistence Pays*, 239–69.

698 Armington, Paul S. 1969. “A Theory of Demand for Products Distinguished by Place of
699 Production (Une Théorie de La Demande de Produits Différenciés d’après Leur Origine)
700 (Una Teoría de La Demanda de Productos Distinguiéndolos Según El Lugar de
701 Producción).” *Staff Papers (International Monetary Fund)* 16 (1): 159–78.
702 <https://doi.org/10.2307/3866403>.

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

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

710 Buzan, J. R., K. Oleson, and M. Huber. 2015. “Implementation and Comparison of a Suite of
711 Heat Stress Metrics within the Community Land Model Version 4.5.” *Geoscientific
712 Model Development* 8 (2): 151–70. <https://doi.org/10.5194/gmd-8-151-2015>.

713 Buzan, Jonathan, and Matthew Huber. 2020. “Moist Heat Stress on a Hotter Earth.” *Annual
714 Review of Earth and Planetary Sciences* 48: 1–30. <https://doi.org/10.1146/annurev-earth-053018-060100>.

715 Cairns, J. E., K. Sonder, P. H. Zaidi, N. Verhulst, G. Mahuku, R. Babu, S. K. Nair, et al. 2012.
716 “Maize Production in a Changing Climate: Impacts, Adaptation, and Mitigation
717 Strategies.” In *Advances in Agronomy*, edited by Donald L. Sparks, 114:1–58. Advances
718 in Agronomy. Academic Press. <https://doi.org/10.1016/B978-0-12-394275-3.00006-7>.

719 Challinor, A. J., J. Watson, D. B. Lobell, S. M. Howden, D. R. Smith, and N. Chhetri. 2014. “A
720 Meta-Analysis of Crop Yield under Climate Change and Adaptation.” *Nature Climate
721 Change* 4 (4): 287–91. <https://doi.org/10.1038/nclimate2153>.

722 Corong, Erwin L., Thomas W. Hertel, Robert McDougall, Marinos E. Tsigas, and Dominique
723 van der Mensbrugghe. 2017. “The Standard GTAP Model, Version 7.” *Journal of Global
724 Economic Analysis* 2 (1): 1–119. <https://doi.org/10.21642/JGEA.020101AF>.

725 Diewert, W.E. 1981. “The Comparative Statics of Industry Long-Run Equilibrium.” *The
726 Canadian Journal of Economics / Revue Canadienne d’Économique* 14 (1): 78–92.

727 FAO. 1995. “Dimensions of Need.” 1995.
728 <http://www.fao.org/3/u8480e/U8480E00.htm#Dimensions%20of%20need>.

729 Fischer, Anthony, Derek Byerlee, and Greg Edmeades. 2004. *Crop Yields and Global Food
730 Security: Will Yield Increase Continue to Feed the World?* Canberra, Australia: ACIAR.

731 Fuglie, K. 2018. “R&D Capital, R&D Spillovers, and Productivity Growth in World
732 Agriculture.” *Applied Economic Perspectives and Policy* 40 (3): 421–44.
733 <https://doi.org/10.1093/aepp/pxx045>.

734 Fuglie, Keith, Madhur Gautam, Aparajita Goyal, and William Maloney. 2020. *Harvesting
735 Prosperity*. Washington D.C.: World Bank Publications.

736

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

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

745 Haqiqi, Iman, Danielle S. Grogan, Thomas W. Hertel, and Wolfram Schlenker. 2019. "Predicting
746 Crop Yields Using Soil Moisture and Heat: An Extension to Schlenker and Roberts
747 (2009)." 291093. 2019 Annual Meeting, July 21-23, Atlanta, Georgia. Agricultural and
748 Applied Economics Association. <https://ideas.repec.org/p/ags/aaea19/291093.html>.

749 Hertel, T.W., U.L.C. Baldos, and van der Mensbrugghe. 2016. "Predicting Long Term Food
750 Demand, Cropland Use and Prices." *Annual Review of Resource Economics* 8: 417–41.

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

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

756 Hussein, Zekarias, T.W. Hertel, and Alla Golub. 2013. "Climate Change Mitigation Policies and
757 Poverty in Developing Countries." *Environmental Research Letters* 8 (3): 035009.
758 <https://doi.org/10.1088/1748-9326/8/3/035009>.

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

761 Jagnani, Maulik, Christopher B. Barrett, Yanyan Liu, and Liangzhi You. 2020. "Within-Season
762 Producer Response to Warmer Temperatures: Defensive Investments by Kenyan
763 Farmers." *Economic Journal* Forthcoming.
764 <https://www.dropbox.com/s/cc7351pkk16yj7b/JBLY.pdf?dl=0>.

765 Key, Nigel, and Stacy Sneeringer. 2014. "Potential Effects of Climate Change on the
766 Productivity of U.S. Dairies." *American Journal of Agricultural Economics* 96 (4): 1136–
767 56. <https://doi.org/10.1093/ajae/aau002>.

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

771 Mader, T. L. 2014. "Animal Welfare Concerns for Cattle Exposed to Adverse Environmental
772 Conditions." *Journal of Animal Science* 92 (12): 5319–5324.

773 McCarl, Bruce A., and Thomas W. Hertel. 2018. "Climate Change as an Agricultural Economics
774 Research Topic." *Applied Economic Perspectives and Policy* 40 (1): 60–78.
775 <https://doi.org/10.1093/aepp/pxp052>.

776 Minard, David, Harwood S. Belding, and James R. Kingston. 1957. "Prevention of Heat
777 Casualties." *Journal of the American Medical Association* 165 (14): 1813–18.
778 <https://doi.org/10.1001/jama.1957.02980320043010>.

779 Moore, Frances, U.L.C. Baldos, and Thomas Hertel. 2017. "Economic Impacts of Climate
780 Change on Agriculture: A Comparison of Process-Based and Statistical Yield Models."
781 *Environmental Research Letters*, April. <https://doi.org/10.1088/1748-9326/aa6eb2>.

782

783 Moore, Frances C, U.L.C. Baldos, Thomas Hertel, and Delavane Diaz. 2017. "New Science of
784 Climate Change Impacts on Agriculture Implies Higher Social Cost of Carbon." *Nature
785 Communications* 8 (1): 1607.

786 Myers, Samuel S., Antonella Zanobetti, Itai Kloog, Peter Huybers, Andrew D. B. Leakey,
787 Arnold Bloom, Eli Carlisle, et al. 2014. "Rising CO₂ Threatens Human Nutrition."
788 *Nature* 510 (7503): 139–42. <https://doi.org/10.1038/nature13179>.

789 Parsons, Ken. 2006. "Heat Stress Standard ISO 7243 and Its Global Application." *Industrial
790 Health* 44 (3): 368–79. <https://doi.org/10.2486/indhealth.44.368>.

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

795 Rosenzweig, C., J.W. Jones, J.L. Hatfield, A.C. Ruane, K.J. Boote, P. Thorburn, J.M. Antle, et
796 al. 2013. "The Agricultural Model Intercomparison and Improvement Project (AgMIP):
797 Protocols and Pilot Studies." *Agricultural and Forest Meteorology* 170 (March): 166–
798 182. <https://doi.org/10.1016/j.agrformet.2012.09.011>.

799 Schlenker, W., and M. J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe
800 Damages to U.S. Crop Yields under Climate Change." *Proceedings of the National
801 Academy of Sciences* 106 (37): 15594–15598. <https://doi.org/10.1073/pnas.0906865106>.

802 Sheahan, Megan, Christopher B. Barrett, and Casey Goldvale. 2017. "Human Health and
803 Pesticide Use in Sub-Saharan Africa." *Agricultural Economics* 48 (S1): 27–41.
804 <https://doi.org/10.1111/agec.12384>.

805 Smith, Matthew R., and Samuel S. Myers. 2018. "Impact of Anthropogenic CO₂ Emissions on
806 Global Human Nutrition." *Nature Climate Change* 8 (9): 834–39.
807 <https://doi.org/10.1038/s41558-018-0253-3>.

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

811 Stevens, Andrew. 2017. "Temperature, Wages and Agricultural Labor Productivity." *Job Market
812 Paper*. https://are.berkeley.edu/sites/default/files/job-candidates/paper/stevens_jmp_jan16.pdf.

813 USDA ERS. 2019. "International Agricultural Productivity." On-line database. 2019.
814 <https://www.ers.usda.gov/data-products/international-agricultural-productivity/>.

815 White, J.W., G. Hoogenboom, B.A. Kimball, and G.W. Wall. 2011. "Methodologies for
816 Simulating Impacts of Climate Change on Crop Production." *Field Crops Research* 124
817 (3): 357–368.

818 Ziska, Lewis H., Dana M. Blumenthal, G. Brett Runion, E. Raymond Hunt Jr, and Hilda Diaz-
819 Soltero. 2011. "Invasive Species and Climate Change: An Agronomic Perspective."
820 *Climatic Change* 105 (1–2): 13–42. <https://doi.org/10.1007/s10584-010-9879-5>.

821

822

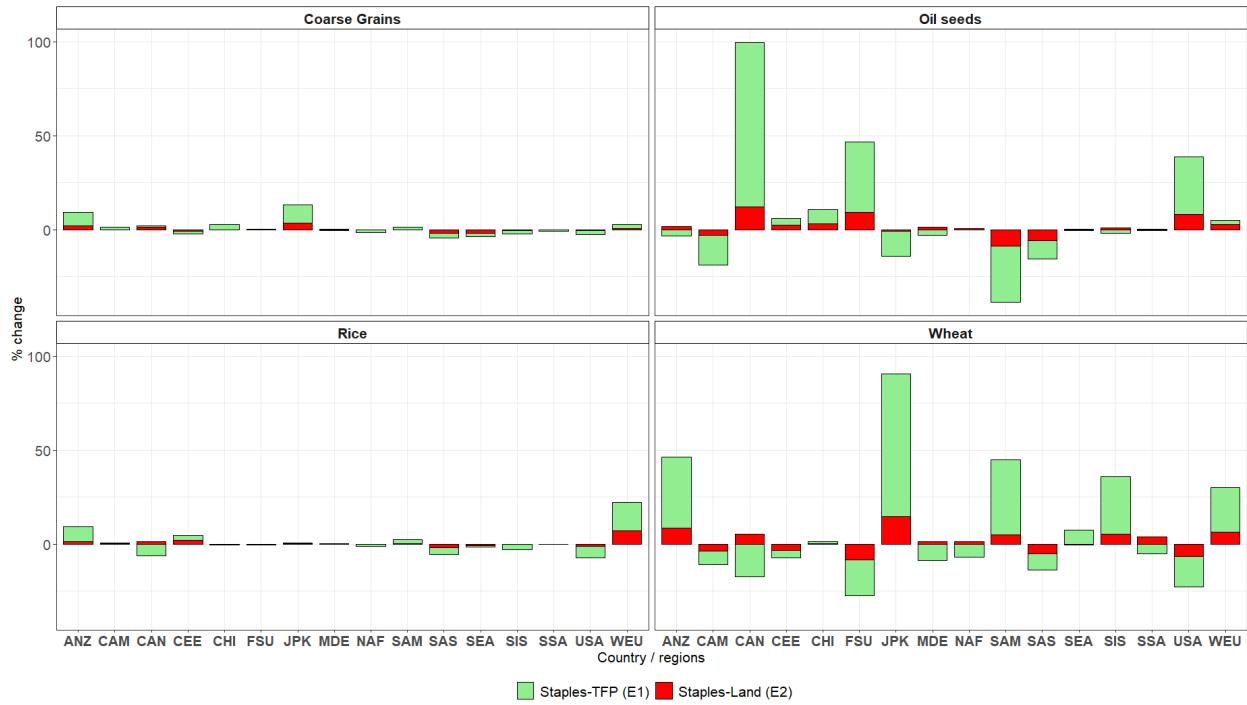
823

**Supplementary Material for
“Climate Impacts on Agriculture: Searching for Keys under the Streetlight”**

By Thomas W. Hertel^{1,2}
and
Cicero Z. de Lima¹

This appendix offers a set of more detailed, pairwise comparisons of the experiments in Table 1 to provide additional insights into how the differential treatment of climate change impacts on agriculture affect regional staples outputs as well as regional welfare. Figures A.1 and A.2 compare regional impacts of experiments E1 and E2, highlighting the difference between treating staple grains yield shocks as total factor production (TFP) shocks vs. partial factor shocks on land productivity. Not surprisingly, the regional output and welfare patterns are quite similar between experiments 1 and 2, with the impacts more muted when yield shocks are interpreted as simply a reduction in land productivity, as opposed to TFP. There are some cases where the sign of the output change is reversed. This is due to the impact on world prices and hence trade.

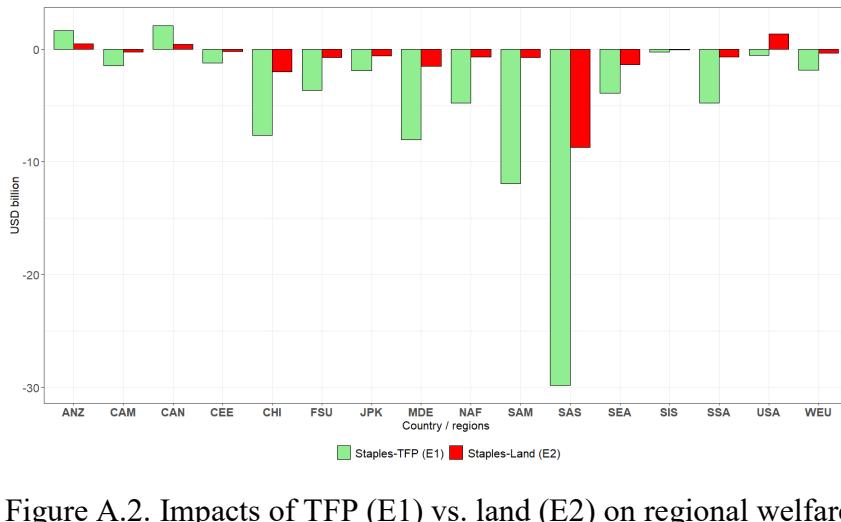
841



842

843 Figure A.1: Impacts of TFP (E1) vs. land (E2) climate impacts on the pattern of Coarse Grains,
844 Oil Seeds, Rice, and Wheat outputs.

845

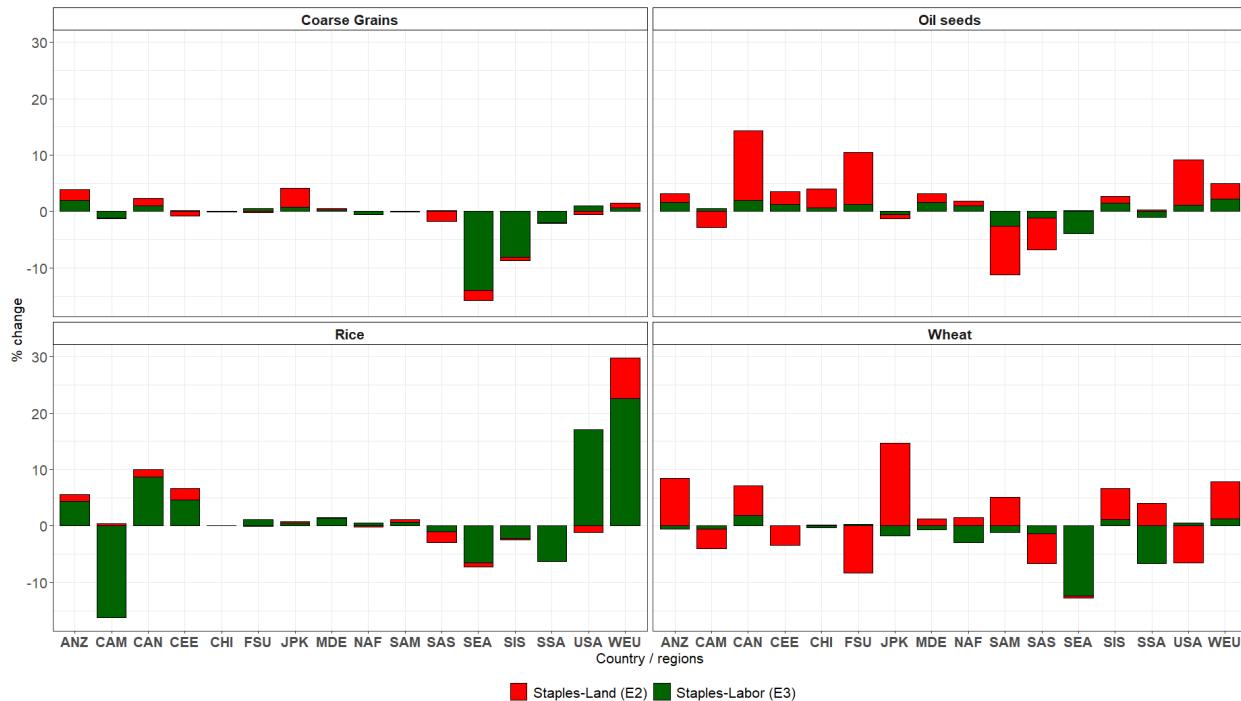


846

847 Figure A.2. Impacts of TFP (E1) vs. land (E2) on regional welfare changes.

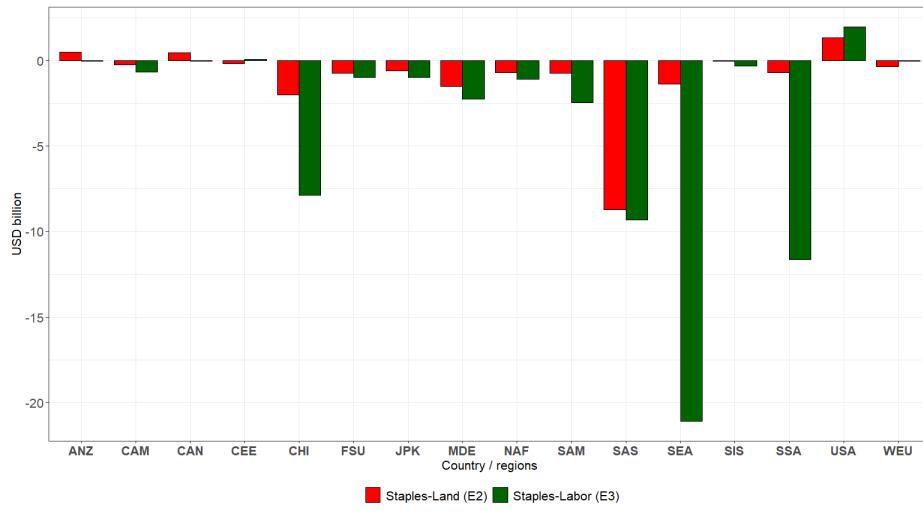
848

849 Figures A.3 and A.4 compare the regional impacts of the partial factor productivity shocks due
 850 to climate-induced reductions in yields (implemented as shocks to land productivity), and labor
 851 capacity (implemented as shocks to labor productivity). The relative sizes of the output impacts
 852 are generally larger for the yield shocks. This reflects the relative immobility of cropland, as
 853 compared to the relatively greater mobility of labor across sectors. In the case of oilseeds and
 854 wheat the output changes from yield shocks are quite dominant (Figure A3). This stands in sharp
 855 contrast to the welfare impacts which tend to be larger in the case of the labor capacity reductions
 856 (Figure A4). Further insight into the welfare comparison can be gained by referring to Figure 6 in
 857 the main text which shows the positive correlation between the size of the partial factor
 858 productivity shocks and the relative importance of the affected inputs. Labor capacity is often
 859 hardest hit in regions where it is most important.



860
 861 Figure A.3: Impacts of land (E2) vs. labor (E3) climate impacts on the pattern of Coarse Grains,
 862 Oil Seeds, Rice, and Wheat outputs.

863



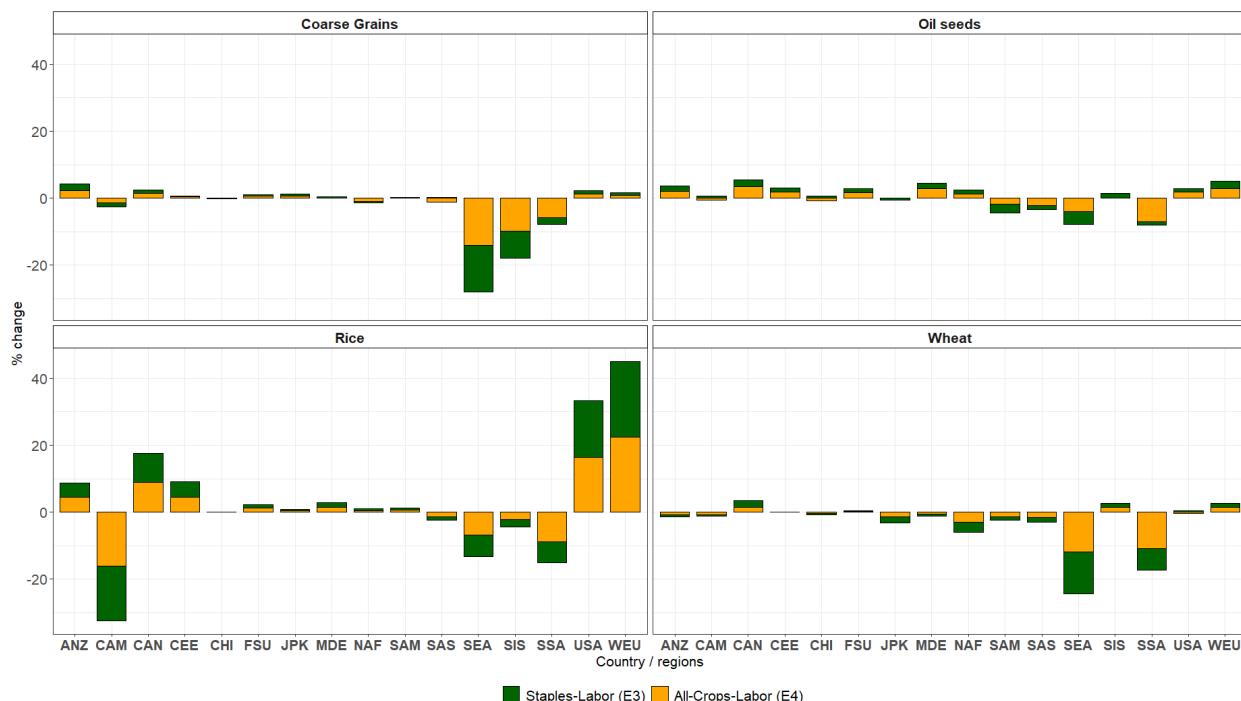
864

865 Figure A.4. Impacts of land (E2) vs. labor (E3) on regional welfare changes.

866

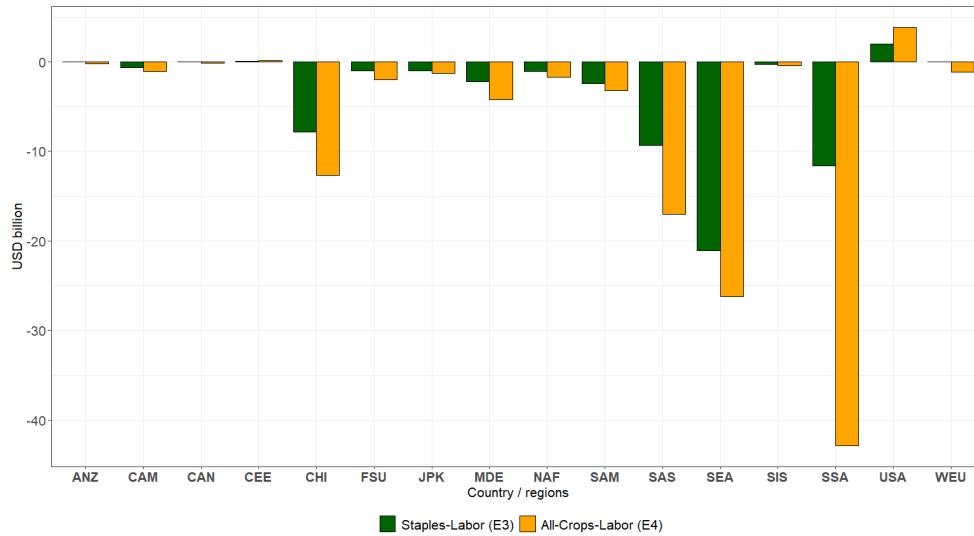
867

868 Figures A.5 and A.6 compare the regional impacts of the partial factor productivity shocks due
 869 to climate-induced reductions in labor capacity when the sectoral coverage of the shocks expands
 870 from staples only (E3) to all crops (E4). Even though the shocks to staples are the same in the two
 871 experiments, the output impacts are magnified when the labor capacity reductions hit all of the
 872 crops. This is because it is no longer possible to divert resources from other crops to staples to
 873 offset the labor productivity reductions in rice, wheat, maize and oilseeds. When it comes to the
 874 welfare impacts, it is hardly surprising that broader adverse impacts carry with them larger welfare
 875 losses and this is the case in Figure A.6.



876
 877 Figure A.5. Impacts of labor (E3) vs. all crops labor (E4) climate impacts on the pattern of
 878 Coarse Grains, Oil Seeds, Rice, and Wheat outputs.

879



880

881 Figure A.6. Impacts of labor (E3) vs. all crops labor (E4) on regional welfare changes.

882